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Impact analysis of electric vehicle demand on demand profile, electricity charges and system emissions of Rochester Institute of Technology

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Impact analysis of electric vehicle demand on demand profile, electricity charges and system emissions of Rochester Institute of Technology

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Akshata Shanbhag

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CERTIFICATE OF APPROVAL

M.S. DEGREE THESIS

The M.S. Degree Thesis of Akshata Shanbhag has been examined and approved by the thesis committee as satisfactory for the thesis requirement for the Master of Science degree

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Abstract

In view of growing concerns of greenhouse gas emissions, electrification in the transportation fleet is expected to increase globally. To accommodate the incoming increase in energy demand from vehicle charging, the existing electrical network should be managed in a way that the load is operated with no electrical instability. Peak demand occurrences which could be measured daily, annually, weekly, monthly or annually should be avoided in order to maintain the health of the electrical network and reduce demand charges billed to the end energy user. Moreover, depending on the emissions factor of the fuel mix used in a region for energy generation the amount of emissions is influenced by the overall network's demand through different times of the day.

This thesis addresses the effects of increasing levels of electric vehicle demand on Rochester Institute of Technology's circuit demand profile, electricity charges and system emissions. The thesis will inform the reader about the potential changes in peak demand behavior, peak months, peak times and peak days as electric vehicle usage increases across campus. In addition, the electric vehicle penetration levels and times at which changes in overall peak demand behavior, electricity charge trend and max emissions through the day occur, will be presented in this thesis paper.

The results obtained through the impact analyses suggested that overall changes in circuit behavior start to become noticeable when electric vehicle users reach 50 times the current number of users on campus. In addition, impacts of electric vehicle demand on the overall circuit's peak occurrences are observed to shift from afternoon to morning hours as fleet electrification increases on campus. Potential electric vehicle charging times to manage the increasing demand on campus and maintaining a leveled overall demand profile, reducing electricity charges and system emissions will be suggested in this paper.

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1 Abbreviations

EV – Electric Vehicle

BEV – Battery Electric Vehicle

PHEV – Plug-in Hybrid Electric Vehicle

HEV – Hybrid Electric Vehicle

VMT – Vehicle Miles Traveled

GHG – Greenhouse Gas

PEV – Plug-in Electric Vehicle

EVSE – Electric Vehicle Supply Equipment

kWh – Kilo-Watt hour

SOC – State of Charge

RIT – Rochester Institute of Technology

PV – Photo-Voltaic

U.S. DOT – United States Department of Transportation

U.S. EIA – United States Energy Information Administration

U.S. DOE – United States Department of Energy

HVAC – Heating, Ventilation and Air-Conditioning

DM – Demand Management

MPG – Miles per Gallon

MW – Mega-Watt

2 Introduction

Electric vehicles represent a new load category for electricity demand and are expected to increase in number rapidly. This increase is partly supported due to the global concern of carbon-dioxide emissions from vehicles with conventional internal combustion engines contributing to the green-house effect. Dogan, et al. (2015) predicts that the plug-in electric vehicles (PEVs) or plug-in hybrid electric vehicles (PHEVs) will account for nearly 62% of the U.S. vehicle fleet by 2050. Hadley, et al. (2009) predicts that the high electric vehicle (EV) penetration in the coming decades could increase stress on the electric grid, leading to a probable installation of new generation plants. The stress on the electric grid may include increase in system peak demand, voltage drops, feeder overloads and more causing network instability. In terms of near-term EV penetration levels, the EV charging demand may likely not strain the United States' generation capacity significantly. This will depend on the times, location and power levels at which the vehicles are being charged (U.S. DOE, 2019). System-wide impacts caused from EV charging may differ from impacts caused on local distribution system on account of high system level diversity factor (Dogan, A. et al., 2015). Diversity factor implies that the maximum demand of a local sub-system, i.e. residential or commercial or industrial building load could be different from the maximum demand of the overall system which encompasses all the loads connected to the network. This means that while the overall distribution system may still hold capacity to withstand additional electrical loads, the load on a local distribution service that powers a single commercial, industrial or residential complex could exceed the system limit. The overall system stress could be impacted due to a single service feeder's failure to withstand further load.

The load behavior of an educational institution could be different from other commercial or industrial load types. To contemplate demand impacts for such a system, Rochester Institute of

Technology (RIT) will be considered as the case study. In this study, the variation in system's demand profile and impacts on system peaks will be analyzed after adding EV load to the existing campus load. With the introduction of EV charging load, the existing system could exhibit higher peak demands. This behavior can introduce imbalances in the local system. Moreover, the repercussions on the institution's monthly electricity charges will follow the demand profile proportionally. The electricity pricing structure is explained in the later part of this section.

The driving range of EVs mainly depends on the battery's state of charge (SOC), battery efficiency and the user's driving habit. Other factors that influence the driving range would include ambient temperature, vehicle weight, battery capacity, vehicle aerodynamic, rolling resistance of vehicle tires and surface terrain. In cities, due to traffic congestion the energy usage for EV charging is high which compels the user to charge the vehicle frequently (Li, W. et al., 2016). This frequent charging can be harmful to the electrical grid depending on the system load level at a certain time. EV charging during peak morning, afternoon, evening or night hours can cause additional peaks in the demand profile of the existing commercial system. Dogan et al. (2015) suggests that with the introduction of EV load, the vehicle charging time, charging power and penetration level, i.e. number of EVs getting charged at the same time are the main factors that impact the system's demand profile, i.e. peak demand occurrences. The daily charging requirements of an EV depend on the distance to be covered, battery capacity, battery efficiency, availability of charging stations and fuel economy of the vehicle (Zhang, P. et al., 2012).

Energy demand could vary with minutes, hours or days over a stipulated time frame, maybe a week, month or year. For meeting these variations in demand different energy generation units are employed. Usually, the cost involved for energy generation to satisfy peak demands is high (Hoehne, C.G. et al., 2016). The energy cost in a region is influenced by the costs involved in building and operating a power plant in that region. The key factors that affect the price of energy include the type of fuel used for energy generation, cost of construction and maintenance of power plants, cost of transmission and distribution of electricity, weather conditions and the government tax regulations in that region (U.S. EIA, 2020). Peak load units which make use of gasoline are generally used to increase the electricity output within a short duration of time. However, these peak load units are less efficient and involve higher costs. Since they are brought into operation occasionally when the energy demand rises, they carry a much higher price per kWh of energy than base load units. Under a demand pricing structure, the time-of-use (TOU) tariff structure is designed to discourage energy use during peak times during the day. TOU pricing involves two main blocks: off-peak and on-peak demand pricing. This pricing is highly influenced by the peak demand during the day (Qian, K. et al., 2011). The commercial and industrial sectors of the economy are significantly impacted by this pricing structure. Usually, on high temperature days peak demands would occur during daytime when the air conditioning load is running nearly at full capacity. Similarly, on low temperature days peak demands would usually occur when heating load is running at full capacity. Under demand pricing in addition to the monthly energy consumption charges, the customer pays for the highest rate of energy used over a certain time period. Typically, monthly demand charges are applied based on the maximum or peak demand (kW) recorded over a 15-minute time interval for that billing month. However, the peak demand can last for a very short duration, i.e. few minutes to a stretch of few hours during the month. This would negatively impact the customer who pays hefty amounts for energy drawn by the system (Khan, A.R. et al., 2016).

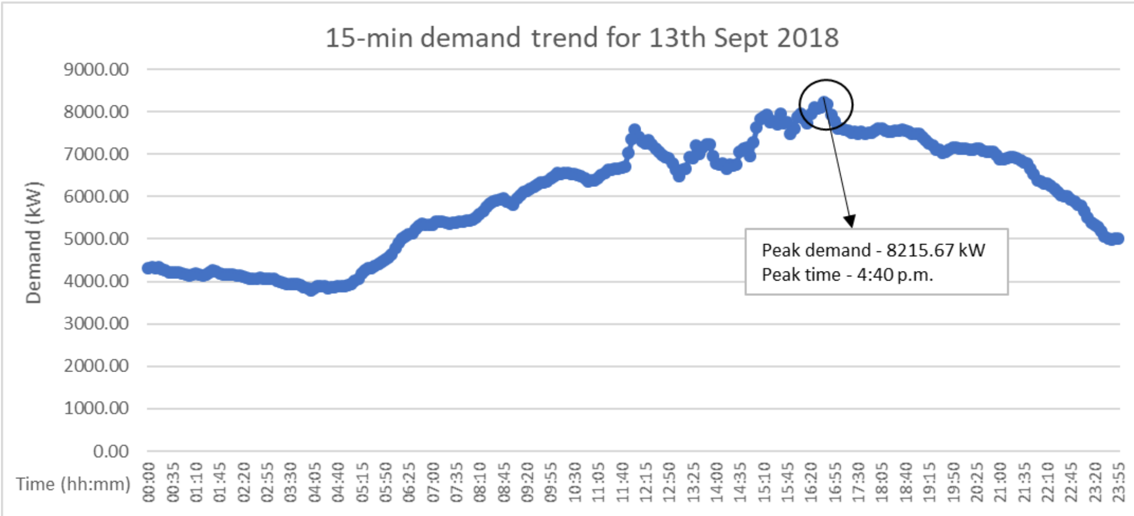


Figure 1 RIT circuit's demand profile

Figure 1 illustrates the demand profile of RIT's circuit for 13th September 2018 when the peak of the month occurred. The peak demand of 8215.67 kW occurred at 4:40 p.m. which is highlighted in the figure. RIT will be applied demand charges based on the 8215.67 kW of power consumed by the campus load. The monthly electricity charges that are billed to any commercial or industrial consumer is influenced by both, the energy consumption charges ($/kWh) and demand charges ($/kW). As per Saxena et al. (2019), the demand charges can constitute up to 70% of RIT's monthly electricity bill. The effect of adding EV demand to the existing RIT's circuit could pose higher impacts on RIT's monthly electricity charges.

The demand pricing structure could encourage the RIT management to guide their EV users to charge their vehicles during off-peak hours. Eventually, this would contribute to managing the overall system's demand profiling. However, considering the high concentration of EV fleet in future, the time spacing between events of EV charging among users and the different work schedules, the EV charging times on campus could overlap with existing circuit's peak demand times. This overlap in times could cause further spikes in the demand profile, thereby influencing RIT's demand charges to further increase. It is unclear on how increasing levels of EV demand would impact both, consumption and demand charges at RIT. Though the system capacity could still withstand EV demand up to a certain level, after a certain level the EV demand could impact the system stability. At what EV level does the overall system behavior change should be addressed. With increasing EV levels it may happen that the month showing maximum peak demand, shifts. Or with the peak demand month being the same, the day or time of peak demand during the month could shift.

At RIT, the EV users are charged an annual permit fee of $300 for utilizing the EV charging stations. No separate charge is applied to the user for drawing electricity from the grid for EV charging. The $300 includes a constant annual vehicle registration fee of $100. With the EV permit, the user is permitted to charge the vehicle up to maximum four hours a day (RIT website, 2020). Under reserved parking, EV users who are RIT's residential students get to charge the vehicle while parked from 5 p.m. to 5 a.m. on weekdays and anytime on weekends (RIT website, 2020). Within this time frame, the user occupancy in campus buildings is usually low. However, with other EV users on campus the vehicle charging demand can significantly influence RIT's overall peak demand occurrences. In this study an average monthly permit fee for EV users that contributes to RIT's monthly electricity charges will be calculated for increasing EV levels.

Moreover, the nature of fuel used for energy generation in a region could vary throughout the day. With this probable variation during on-peak and off-peak demand periods, there could be trade-offs in overall system emissions. The level of emissions associated with EV charging is influenced by the carbon intensity of the fuel mix for energy generation, time of day when the vehicle is charged, ratio of electric to gasoline miles in the case of PHEV and the efficiency of the vehicle, i.e. miles per gallon equivalent (McLaren, J. et al., 2016). In addition to analyzing the impacts of

EV demand on RIT system's demand profile, the impact on overall system level emissions will also be studied.

Probable outcomes of adding EV demand to the existing circuit could generally include variation in system's overall demand profile, increase in RIT's monthly electricity charges and variations in overall system emissions. A detailed analysis of the three impact categories is elaborated in the further sections.

Several questions would arise while considering an increasing number of EV users on campus. These questions could include: At what average EV penetration level, does the monthly demand profile alter? Does RIT need to think about different approaches to enforce guidelines or rules to EV users to reduce the impact on the existing network? Does the current EV user permit fee seem a fair price to contribute towards RIT's monthly electricity bill? Are there specific months during the calendar year that need more attention by RIT's facilities management for carrying out load profiling strategies? Does the month which reflects the highest peak demand during the year match with the month in which maximum system emissions occur? Such thoughts and questions are evaluated and discussed in this thesis paper.

The further sections in this thesis paper will cover: Section 3 – 'Background' which entails a general description on EVs, vehicle charging characteristics, charging impacts on demand stability and emissions, followed by information on RIT's EV charging stations and a past case study; Section 4 – 'Problem statement' elaborating on objectives of the thesis study; Section 5 – 'Literature review' presenting short descriptions of previous case studies on EV charging impacts on demand profiles and electricity charges; Section 6 – 'Methodology' for conducting the thesis analyses; Section 7 – 'Results and Discussion' covering the findings, potential reasonings and solution strategies for reducing impacts of increasing EV demand on the three impact categories;

Section 8 – 'Conclusion and Future work' will summarize the findings and aspects not covered under this thesis work and Section 9 – References to cite findings based on other research studies.

3 Background

This section will inform the reader about the following: background on vehicle electrification, description of plug-in EVs (PEVs) and their charging characteristics, vehicle charging impacts on system stability and greenhouse gas emissions, a case study on RIT's peak load forecasting for reducing demand charges and lastly, the current EV charging infrastructure on RIT campus.

Globally, the political pressure to reduce GHG emissions and use of conventional sources of energy for energy generation has driven the market share of PEVs to increase in the recent decades (Jochem et al., 2015). This is mainly because of the technological progress in the area of batteries used to store electric charge (Jochem et al., 2015).

3.1 Vehicle Description

Pure EVs and plug-in hybrid EVs (PHEVs) come under the section of PEVs where PEVs derive all or a part of their power from the energy supplied by the electric grid. EVs are vehicles that use one or more electric motors. These motors are powered by the electricity stored in the EV batteries. The electric energy is derived by plugging them at charging points connected to the grid. They use no petroleum-based fuel while in motion and hence give out no tailpipe emissions into the atmosphere (Cities, 2012). However PHEVs, in addition to electric energy in the battery also have the provision of a petroleum based fuel to power the conventional or internal combustion engine (Cities, 2012). PHEVs have the advantage of switching to conventional mode on electric charge depletion, hence lowering range anxiety of the vehicle user.

The use of EVs and PHEVs reduce the usage of petroleum, thereby potentially reducing the cost for the user (Cities, 2012).

3.2 PEV charging

Charging a PEV requires supply equipment which differs based on the rate at which it charges the vehicle. The time required to charge a fully depleted battery can range from less than 30 minutes to almost a full day (Cities, 2012). This rate of energy charging depends on factors such as vehicle type, battery type and the type of charging equipment (Cities, 2012). The main types of charging are Level 1, Level 2 and DC fast charging. Level 1 is a slower rate of charging that gives 2 to 5 miles of range per hour of charging at a 120 V charging outlet (Cities, 2012). Level 2 is comparatively more efficient giving the vehicle 10 to 20 miles of range per hour of charging at a voltage level of 240 V at residential locations and 208 V for commercial applications (Cities, 2012). DC level fast charging is the most efficient and gives the vehicle 60 to 80 miles of range per 20 minutes of charging through an ac input of 480 V to the electric vehicle supply equipment (EVSE) wherein the power gets converted to DC (Cities, 2012). In most public places such as commercial complexes and offices, Level 2 charging equipment is installed due to their higher charging power, facilitating shorter charging duration (Cities, 2012). This in-turn improves the charging rate of EV fleet.

3.2.1 Impacts of PEV charging on system stability and electricity charges

EV charging demand depends on the number of EVs, the time duration of battery charging, and the initial state-of-charge of battery during the vehicle charging process. These factors usually have a sense of randomness. However, the general pattern is influenced by the region's traffic habits at that time and the electricity rate structure (Qian, K. et al., 2011). The overall demand profile of an electric system changes due to the mass introduction of EV charging (He, Y. et al., 2012). The randomness in users' charging behavior could cause system instability by causing additional peaks to the existing system peak demand. In addition, major system performance issues could arise due to the large battery size of EVs which consumes a significant amount of energy (Hosseini, S.S. et al., 2013). In addition, reduced electricity charges applied by the utility company can influence EV users to charge their vehicles during off-peak demand periods. This could result in simultaneous charging of multiple EVs at a time, thereby increasing the peak demand levels. Considering EV demand is important to design an optimal electricity pricing schedule that will satisfy both, the utility company and the customer (Dubey, A. et al., 2015).

3.2.2 Impacts of PEV charging on GHG emissions

EVs are considered as a technology that enable a transition towards a low carbon mobility future. However, there are many factors that influence the amount of emissions associated with EV charging. These factors mainly source from the energy generation phase and vehicle usage phase (Abdul-Manan, A.F.N. 2015). GHG emissions mainly depend on: (1) fuel type used for the electricity generation; (2) the driving cycle type, i.e. whether city or highway driving; (3) the range the EV offers with the assumed battery's state of charge; (4) operating mode of the vehicle, i.e. whether electric or gasoline in the case of PHEV and; (5) efficiency of the vehicle, i.e. kWh/100 mi in electric mode and MPG in conventional mode (Abdul-Manan, A.F.N., 2015).

The emissions associated with EVs are basically Well-to-Tank, i.e. from fuel extraction through power distribution to the charging outlet. In the case of PHEVs, tailpipe emissions will occur when driven in conventional mode.

In an electricity system with high renewable energy mix, the net emissions from EVs can be very low (Sioshansi, R. et al., 2010). However, In regions where coal dependency is high, the charging of EVs could be associated with higher emissions than conventional internal combustion engines

(Woo, J. et al., 2017). The fuel mix used for electricity generation in a region can vary throughout the day. Amidst this variation, the time at which the vehicles are charged is an important factor for net emissions (Sioshansi, R. et al., 2010).

In New York (NY) state, around nine-tenths of the electricity is sourced from natural gas, nuclear power, and hydroelectricity (U.S. E.I.A, 2017). More than half of the generation capacity is at natural gas fired power plants and about two-thirds capacity is at units with duel-fuel capability that use either natural gas or petroleum (U.S. E.I.A, 2018). In NY state, electricity regulators require the dual-fuel units to be ready to switch to petroleum in the event of natural gas supply interruption during winter months (N.Y. Power trends 2017, 2019). Depending on the energy demand during the day, the carbon levels associated with the fuel used for the region's electricity generation will vary, thereby influencing emissions. In addition, the non-uniform pattern of EV charging will further impact the overall emission levels through the day.

The hourly emissions intensity is not consistent and varies regionally, by time of day, daily and seasonally. Developing general guidelines on when lowest emissions will occur during the day is not a practical solution for lowering GHG emissions sourced from vehicle charging (McLaren, J. et al., 2016). McLaren, 2016 suggests that the respective regions' yearly average grid emissions can be used as a guide to estimate the EV users' contribution towards GHG emissions. Similarly, with hourly daily emissions factor during a month the average time of day during which maximum emissions occur can be understood. Modifications in time scheduling for vehicle charging at different locations could be thereby suggested.

3.3 Basic terminology and definitions

Terms such as peak demand, peak days and EV levels will be commonly used for this thesis study. The detailed terminologies are presented in the Methodology section of the paper.

Peak demand is the largest electrical power drawn from electricity grid. Peak demand can last for a few minutes to over hours. It can be characterized hourly, daily, monthly, annually or seasonally. Though the peak demand is characterized by the maximum power drawn from the grid during a certain time, there could be other times during the day when high energy demand periods occur. These can be characterized by a baseline value which will be used in this thesis study. Peak times will occur when these high energy demand values exceed the baseline value.

As explained in Section 2 of the paper, usually the monthly demand charges are based on the peak demand recorded over a 15-min interval. Mostly, commercial and industrial users experience demand charges which typically contribute between 30 and 70 percent of the monthly electricity bill (Stem Energy Superintelligence, 2019). In order to reduce demand charges, the users should follow a uniform energy consumption pattern during the day.

3.4 RIT Peak Load Case Study

With the implementation of different peak load forecasting algorithms, Saxena et al. (2019) shows that heavy demand charges worth $80000 annually billed to RIT could be saved for a single sub-meter encompassing the energy consumption of 14 campus buildings. Using peak time definition as elaborated in Section 3.3, in this thesis peak days will be analyzed after adding EV demand to an integrated set of campus loads connected to RIT's circuit.

To carry out this study, RIT's circuit A will be considered. To understand an example, consider Figure 2 that depicts the circuit A and EV demand profile for Sept 2018. Circuit A peak demand of 8670 kW occurred on 13th Sept at 4 p.m. whereas the EV demand peak corresponding to 30.40 kW occurred on 11th Sept and lasted for ten minutes in the time frame 10:15 a.m. to 10:25 a.m. It is observed that RIT's circuit A is heavily loaded in the afternoon whereas the EV users seem to load the network in the morning hours. Considering circuit A demand and EV demand separately, the peak demands have a time gap of around 5.5 hours.

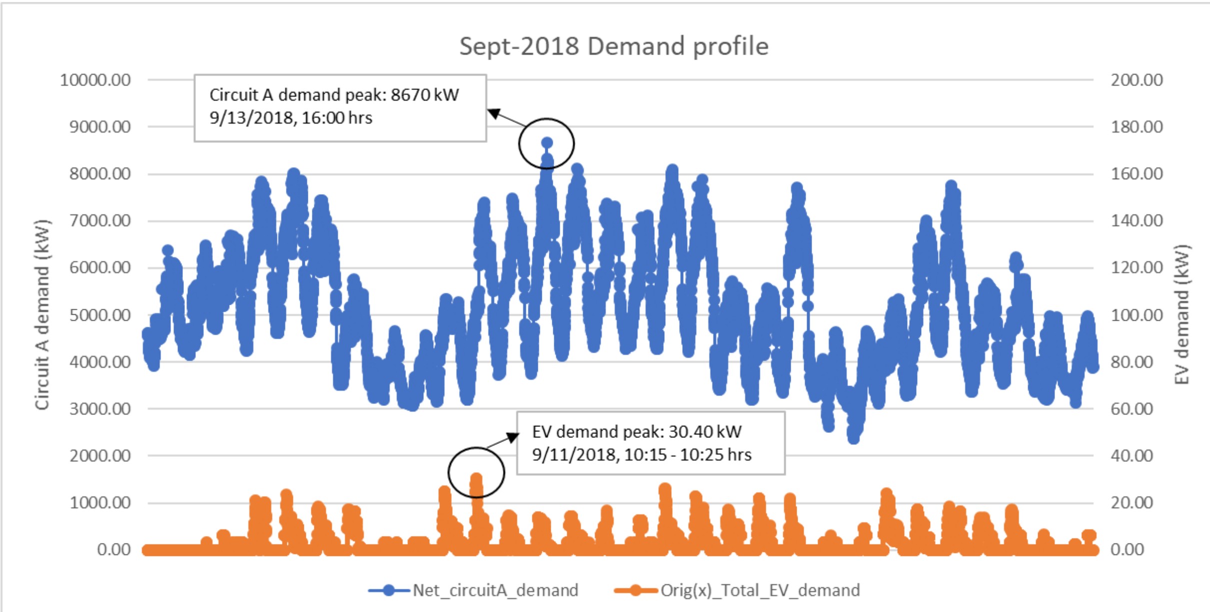
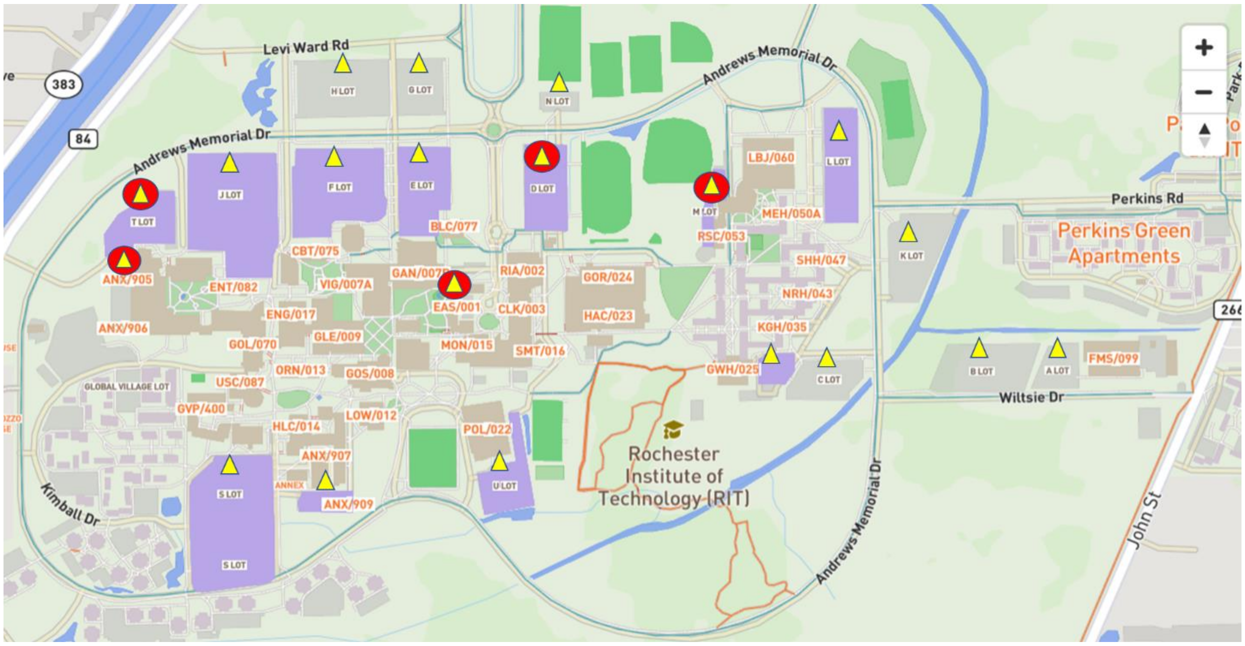


Figure 2 EV versus A1 circuit demand profile for 5th May 2017

Based on this example, the impact analysis of the overall system after adding EV demand to circuit A's demand was carried out. The impact on overall peak time shift from circuit A was studied. In addition, with increasing EV users on campus the impact on daily peak time shift, monthly electricity charges and system emissions were analyzed.

3.5 Charging Stations on RIT campus

From a total 18 parking lots, 5 lots: T, D, M, admin and CIMS West have the provision of EV charging stations as shown in Figure 3. The charging stations involve Level 1, Level 2 and Tesla chargers.



denotes parking lot with provision of EV charging

denotes RIT campus parking lot

Figure 3 RIT Campus Parking Lots (RIT website, 2020)

The EV charging segregation for the five parking lots are as follows: D lot - 3 Level 2 chargers with 12 parking spaces, M lot - 1 Level 2 charger with 2 parking spaces, T lot - 4 Level 2 chargers and 1 Level 1 charger with total 11 parking spaces, admin lot - 1 Level 2 charger with 2 parking spaces and CIMS West lot - 1 Tesla charger. To summarize, RIT campus has a total count of 28 parking spaces for EV users. The charging stations are open to RIT community members and residential students under respective parking permit conditions. Residential students have the access to the charging stations from 5 p.m. to 5 a.m. on weekdays and anytime during the weekends (RIT website, 2020).

4 Problem Statement

EV users could charge their vehicles based on the availability of a charging point at any location. However, the charging is carried out without considering the EV charging contribution towards the system demand and fuel emissions from the associated electricity generation. A disorganized EV charging pattern can cause additional peaks in the existing demand profile thereby leading to system instability. Moreover, the monthly electricity demand charges billed to the customer (in this case RIT) can further increase due to increase in peak demand levels. In addition, the fuel mix used for generating electricity to operate the daily varying energy demands of a region influences the amount of carbon emissions (kg CO_2/kWh).

Research has been done on impacts of EV charging on different loads such as home, workplace and public places. This is discussed in Section 5 of the paper. However, the impact may differ for an educational institution which has different work and time of day schedules which needs further research. At RIT the demand profile of an existing circuit may or may not change significantly by adding EV demand. As EV infrastructure increases on campus, the overall peak demand behavior could change.

The impact of increasing EV demand on RIT's monthly electricity bills can be significant. Currently, the monthly permit fee applied to the EV user may or may not suffice for recovering the electricity consumption and demand charges contributed solely by EV charging. Identifying appropriate permit fees as EV levels increase on campus is important to ensure that both, consumers and energy bill payers are happy.

In terms of carbon emissions from EV charging, the fuel mix used at the electricity generation source in a region influences the amount of CO_2 that is emitted. After adding increasing EV level demands to a circuit demand, the carbon emissions could increase. In most regions of the U.S., the dominant marginal fuel source is natural gas. In addition, in the northeast region of the U.S. petroleum is a significant marginal fuel source (Siler-Evans, K. et al., 2012). Based on the type and amount of fuel dispatched to operate the hourly demand, the emissions will be directly influenced. Lower levels of EV demand may not pose significant increase in CO_2 emissions. The impacts could be high as the overall demand increases with increasing EV levels. With such potential observations, we can arrive at ideas about times of the day which are not suitable for EV charging due to the existing circuit's high demand. Thereby, system emissions contributed by EV charging could be controlled by altering EV users' charging times.

With this thesis, we aim to achieve three objectives by analyzing data from July 2018 to June 2019 for RIT's circuit A:

- Analyze the impact of increasing EV level demands in circuit A demand profiles. Emphasis will be placed on impact of EV demands on circuit A peak demand and associated peak demand days.
- Analyze the impact of increasing EV level demands on RIT's electricity charges that will include energy consumption and demand charges. Emphasis will also be laid on determining a fair EV permit fee at varying EV levels.
- Analyze the impact of increasing EV level demands on RIT's system emissions.

With these analyses, educational institutions such as RIT could implement appropriate time-based demand response strategies. This would facilitate a reduction in additional peaks in overall energy demand. In turn additional monthly electricity demand charges could be negated, and system emissions could be lowered.

5 Literature Review

In this section, impacts of EV demand on the demands of different load categories will be understood for different times of the day and locations. In addition, the impacts on associated demand charges will also be elaborated. These case studies will be related and compared with the ideas and impact studies of this thesis paper.

Dogan et al. (2015) investigated the impact of different EV charging strategies on the peak demand of a residential distribution comprising of 1000 houses for Yakima, WA. Four EV penetration levels: 10%, 20%, 30%, 50% and two charging modes: normal charge mode of 120 V at 1.9 kW and quick charge mode of 240 V at 3.3 kW were considered. In quick charge mode, by modifying the EV charging strategies to off-peak hours the EV demand impact on system peak load can be avoided for 10% EV penetration. Beyond 10% the system peak load tends to increase. At 50% EV penetration the peak load increases by 10.2%. If EV charging load is shifted to off-peak hours the system load factor which is the ratio of the system's average demand to peak demand, can be improved at a reduced EV penetration level (Dogan, A. et al., 2015). In lines with this study, we will analyze the impacts of increasing EV levels on RIT's circuit A demand. Times during the day when circuit A peak and EV peak demands occur will be analyzed. When increasing levels of EV demand are added to circuit A's, the impact on overall peak time will be observed. EV charging access to RIT's residential students from 5 p.m. to 5 a.m. on weekdays may help in lowering the overall peak demand. But with no present enforced rules for other EV users on campus, the overall demand profile may experience further spikes in peak demand especially during daytime hours when user occupancy is high.

Qian et al. (2011) presented the impact of different battery charging scenarios on a U.K. distribution system. The loads are divided into three main categories: residential, industrial and commercial. This is done since the EV charging load is unlikely to grow uniformly across the three load categories and hence should be analyzed separately. The analysis was carried out under different scenarios among which uncontrolled domestic charging is considered as the worst-case scenario. In this scenario, all the vehicles begin their charging event at the same time. An overall EV penetration of 10% and 20% would lead to a 17.9% and 35.8% increase in daily peak demand, respectively.

Table 1 shows the percentage increase in peak load for industrial and commercial load categories for uncontrolled public charging scenario:

Table 1 Percent increase in peak load for uncontrolled public charging (Qian K. et al., 2011)

Load Category	Industrial	Commercial
10% EV penetration	5.9%	7.3%
20% EV penetration	11.8%	14.6%

Under uncontrolled public charging scenario, EV charging is allowed during the working hours at the workplace. The data suggests that under these two load categories, EV charging load naturally meets peak load if all EVs start charging at the same time, when the users arrive at workplace in the morning. Similarly, this research will aim to analyze whether EV users on campus contribute towards the existing circuit A's peak demand profile. If this scenario takes place, the overall peak demand will further load RIT's network and could impact the electrical network's healthy operation. Lastly, Qian et al. (2011) also mentions that enough generation capacity does not directly relate to the distribution system's capability of handling EV load. Though there is enough energy generated to operate the overall system demand, the service feeder might not be able to charge the plugged in EV batteries due to overload conditions. The energy demand constraints need to be analyzed at the distribution phase. In this study, the behavior of RIT's overall demand involving circuit A will be analyzed when the demand profiles will be plotted for different levels of EV penetration.

Furthermore, Awadallah et al. (2016) presents the impacts of EV charging load on the capacity of distribution feeders and transformers of an urban utility in a residential neighborhood of Toronto. The worst-case scenario is when all EV chargers are connected to the system during peak summer and winter loads. For EV chargers of 3.3 kW rating, no system overloading occurs at any EV penetration level. However, the case differs for EV chargers of 6.6 kW rating. Highest transformer overload of 64.3% occurs at 100% EV penetration, during maximum load hour 8 p.m. to 9 p.m. In the case of RIT, the highest user occupancy and electricity usage will most likely load the network during day or afternoon hours with additional EV demand. According to Awadallah et al. (2016), the major outcome was that EV chargers of higher rating, i.e. 6.6 kW and above significantly impact the system stability. Network upgrades are required to power even moderate levels of EV penetration at higher EV charger ratings. For this study it will be considered that circuit A possesses the capacity to charge EVs with battery ratings of 3.3 kW and 6.6 kW. Also, summertime is the most critical since the ambient temperature limits the overloading capacity of the system components, thereby reducing the overall network efficiency (Awadallah, M.A. et al., 2016). Similarly, in the case of RIT the month that exhibits highest overall peak demand will be observed for increasing levels of EV demand.

Weiller (2011) studies the effects of different charging behaviors of PHEVs on the electricity grid for different times of the day and locations: home, workplace, shopping centers and restaurants in the United States. The study suggests that the maximum amplitude of additional PHEV charging load does not impose a higher load on the electrical grid compared to other home appliances. Usually, charging at any location increases the load between 9 a.m. and 9 p.m., especially at morning and afternoon peaks when users are commuting to and from their workplaces. Out of the considered locations, highest energy demand for vehicle charging occurs at home mainly in the afternoon between 4 p.m. and 7 p.m. Moreover, though weekends are usually off-peak periods due to lesser work activities the peak power from vehicle charging occurs on weekends at all locations (Weiller, C., 2011). This could be the case because EV chargers are plugged-in for longer durations due to no limitations on work time schedules, especially at workplace and home locations. According to Weiller (2011), at commercial locations EV charging does not significantly impact the electrical system in terms of average energy use. However, EV charging in locations like shopping areas could cause peak load instances during the weekends. Considering RIT's residential students have access to EV charging any time on the weekends, similar peak demand behavior may or may not be observed on RIT campus.

Sehar et al. (2017) studies the impacts of fast PEV charging on a retail building's demand profile. Typically, in the U.S. major end-use loads in retail (non-mall) buildings consume about 26% of total electricity for lighting and 34% for Heating, Ventilation and Air-conditioning (U.S. EIA, 2012). In the methodology presented by Sehar et al. (2017), PEV owners are given priority for vehicle charging over building load when the energy is supplied by photo-voltaic (PV) technology. At the time of PV energy insufficiency, demand management (DM) of lighting and HVAC is performed for reducing the building's electricty demand to satisfy vehicle charging demand. Simulation results presented by Sehar et al. (2017) show that the overall building's energy consumption is high from 6 a.m. to 9 p.m. with peak time occurring at 7:50 p.m. due to additional exterior lighting load. With added EV demand and the inclusion of PV energy, the building peak shifts to later evening hours. However, the overall peak demand in the evening is lower than the overall afternoon peak demand with no PV energy (Sehar, F. et al., 2017). This is because of the building's high cooling demand is further impacted by EV demand during afternoon hours. Moreover, the random pattern of vehicle charging gives rise to new building peak demands. This randomness in EV charging behavior will be covered in the thesis study by carrying out replications of shuffling of days for each month. This is explained in Section 0. Moreover, Sehar et al. (2017) discusses that fast EV charging increases the building's peak load, in-turn leading to increased peak demand charges. In order to lower the overall building's peak demand while accounting for the randomness in EV charging behavior, the combination of stringent DM and PV energy must be implemented. With this strategy, PEV penetration can be increased from 7% to an average of 38% and can be accommodated by the network (Sehar, F. et al.,2017).

With the inclusion of lighting and HVAC loads, RIT should consider employing demand response strategies to reduce the electricity consumption during peak hours. In addition, with the smart use of the 2 MW solar energy generation, demand profiling can be managed thereby lowering demand charges.

The literature review has indicated various scenarios of EV demand impacting network stability, peak demand profiles and peak times for residential, industrial and commercial loads of large network systems. However, less focus has been applied to EV charging impacts for academic institutions. Also, there has been little emphasis on peak time impacts for different EV penetration levels on a smaller electrical system. The following section will present the methodology used for carrying out the EV impact analyses on RIT's circuit network.

6 Methodology

This section will review the assumptions and framework designed to achieve the thesis objectives explained in the Problem Statement.

6.1 Data processing steps

The following explanation provides details of the complete data streamlining processes to carry out the analyses.

6.1.1 Data Collection

Currently, RIT has two separately billed circuits: A and B. For this thesis work, data for circuit A was utilized. Data for circuit A that captures the energy usage of 21 university buildings including academic, on-campus housings and the 2 mega-watt (MW) solar field were collected. Additionally, the demand data of 10 EV charging stations on campus were obtained. The two data sets were obtained from the WebCTRL Energy Management System of RIT (RIT WebCTRL, online).

Circuit A data contained 5-min energy demand records in kW for sub-circuits A1, A2 and A3. Sub-circuit A3 provided the data of the 2 MW solar field that provides power to circuit A. The EV demand data file contained 5-min energy demand records for each charging station. Both datasets covered the time frame: 1st July 2018 at 00:00 hrs to 26th June 2019 at 23:55 hrs, i.e. 103,968 5-min time records. The notations for the 5-min demand data for circuit A and base level EVs is shown in Table 2.

Table 2 Notations for 5-min circuit A and EV demand data

Notation	Notation description	Time window	UoM
$d_{A5,i,j}$	circuit A demand at time 'i' and month 'j'	5-min	kW
$d_{E5,i,j}$	EV demand for base EV level at time 'i' and month 'j'	5-min	kW

6.1.2 Data Cleansing

Demand records corresponding to 340 5-min time intervals showed ambiguity in the circuit A file. Within these, either sub-circuit A1, A2 or A3 data individually or all three had either missing or unrecorded (null) values. These individual ambiguous values were imputed based on one of the following two logics:

Logic 1: The average of preceding 10 energy demand values was calculated. Table 3 shows an example of logic 1 calculation for an unrecorded demand value of sub-circuit A1 as highlighted. In this case, the sub-circuit energy demand at 23:00 hrs of 15th Dec 2018, was calculated using the generic equation 1.

$$d_{A5,i,j} = \left[\frac{\sum_{a=i-50min}^{a=i-5min} d_{A5,i,j}}{10}\right] \tag{1}$$

In this case, the missing demand record at 23:00 hrs for 15th Dec 2018 is given by equation 1a.

$$d_{A5,12/15/2018\ 23:00,Dec\ 2018} = \left[\frac{\sum_{12/15/2018\ 22:10}^{12/15/2018\ 22:55} d_{A5,i,Dec\ 2018}}{10}\right] \tag{1a}$$

Table 3 Example depicting logic 1 calculation for unrecorded energy demand value

Time	A1 kW Demand
12/15/2018 22:10	2,421.00
12/15/2018 22:15	2,456.00
12/15/2018 22:20	2,467.00
12/15/2018 22:25	2,427.00
12/15/2018 22:30	2,405.00
12/15/2018 22:35	2,393.00
12/15/2018 22:40	2,411.00
12/15/2018 22:45	2,414.00
12/15/2018 22:50	2,494.00
12/15/2018 22:55	2,382.00
12/15/2018 23:00	2,427.00

Logic 2: The average of the preceding and succeeding days' 5-min demand values corresponding to the missing or unrecorded value's 5-min time interval and day was calculated. Table 4 shows an example of logic 2 calculation for unrecorded demand values

of sub-circuits A1, A2 and A3 as highlighted. In this case the three energy demands at 5:25 hrs of 16th Dec 2018 were calculated using generic equation 2.

$$d_{A5,i\,j} = \left[\frac{d_{A5,i-24hrs,j} + d_{A5,i+24hrs,j}}{2}\right] \tag{2}$$

In this case, the missing demand records at 5:25 hrs for 16th Dec 2018 is given by equation 2a.

$$d_{A5,12/16/2018\ 5:25,Dec\ 2018} = \left[\frac{d_{A5,12/15/2018\ \ 5:25,Dec\ 2018} + d_{A5,12/17/2018\ \ 5:25,Dec\ 2018}}{2}\right] \tag{2a}$$

Table 4 Example depicting logic 2 calculation for unrecorded energy demand value

Time	A1 kW Demand	A2 kW Demand	A3 kW Demand	Net A kW Demand
12/15/2018 5:25	2050.00	1640.00	0.00	3690.00
12/16/2018 5:25	2151.50	1738.50	0.00	3890.00
12/17/2018 5:25	2253.00	1837.00	0.00	4090.00

For cases where records were missing or unrecorded for over 10 consecutive 5-min intervals, logic 2 was favored as the imputation method.

6.1.3 Data compilation

The 5-min energy demands of the 10 EV charging stations were added to get the total EV demand corresponding to base EV level. Similarly, sub-circuits A1, A2 and A3 were added to get the net circuit A demand. This was carried out for the period 1st July 2018 at 00:00 hrs to 26th June 2019 at 23:55 hrs. The 103,968 5-min EV demands and circuit A demands were then separately added to get the overall 5-min demands for base EV level. The equation for 5-min overall base EV level demand is given by equation 3.

$$d_{D5,i,j} = [d_{A5,i,j} + d_{E5,i,j}]\ \forall\ \mathrm{i} \in \text{month j} \tag{3}$$

The final dataset containing 5-min circuit A and overall demands for base EV level was utilized for carrying out data calculations. Additional steps were carried out particularly for conducting impact analysis of increasing EV level demands on circuit A peak demand. This is explained in section 0.

6.1.4 Data calculations

6.1.4.1 Impact of increasing levels of EV demand on circuit A peak demand

With increasing EV demand on RIT's circuit A, the average daily shift in overall peak time from circuit A peak time was analyzed. Moreover, the shift in month reflecting the maximum peak in the duration July 2018 to June 2019 was observed. With increasing EV levels, the common peak days and new peak days with reference to circuit A was also determined. Lastly, months reflecting maximum difference in peak demands from the demand limiting factors for increasing EV levels was studied for gaining ideas for demand response strategies in future.

6.1.4.1.1 Assumptions

- The EV charging pattern is different during weekdays and weekends and may also differ month to month.
- The net circuit A demand considers the energy produced by the 2 MW solar field.
- Demand charges for a month are based on the 15-min rolling peak demand.
- As EV infrastructure levels increase on campus, we assume the EV demand profiles to scale proportionally.

6.1.4.1.2 Notations

Table 5 provides a description of the variables used for carrying out the mathematical operations for EV impact analysis on circuit A peak demand.

Table 5 Notations to carry out peak demand calculations

Notation	Notation description	Time window	UoM
$d_{A15,i,j}$	rolling circuit A demand at time 'i' and month 'j'	15-min	kW
$d_{E15,l,i,j}$	rolling EV demand for EV level 'l' at time 'i' and month 'j'	15-min	kW
$d_{D15,l,i,j}$	rolling overall demand for EV level 'l' at time 'i' and month 'j'	15-min	kW
$D_{A15,j}$	circuit A peak demand in month 'j'	15-min	kW
$D_{D15,l,j}$	overall peak demand for EV level 'l' in month 'j'	15-min	kW

6.1.4.1.3 Mathematical operations

6.1.4.1.3.1 Creating replications for randomizing days

The daily EV charging pattern varies during the week. The variability in the use of charging stations was captured by simulating multiple EV charging usage patterns. To create these replications for each month in the duration July 2018 to June 2019, the following procedure was performed.

The historical 5-min EV demands were split into weekdays and weekends. For example, for Jan 2019:

Weekdays: [1, 2, 3, 4, 7, 8, 9, 10, 11, 14, 15, 16, 17, 18, 21, 22, 23, 24, 25, 28, 29, 30, 31]

Weekends: [5, 6, 12, 13, 26, 27]

15 random permutations of the original list were created. For example, replication 1 would read as:

Weekdays: [17, 30, 3, 23, 7, 4, 9, 22, 11, 14, 31, 24, 1, 18, 21, 10, 8, 26, 4, 28, 29, 2, 15]

Weekends: [27, 26, 12, 6, 13, 5]

So, for replication 1 the 5-min demands that occurred on 17th Jan, would be used as the demands for the first weekday, those of 30th Jan would be used for second weekday and so on. Similarly, for weekends 5-min demands that occurred on 27th Jan would be used as demands for the first weekend and so on.

For each replication, the 5-min base level EV demands were multiplied with different levels. These 5-min EV demands at different levels were individually added to the original 5-min circuit A demands to get the respective overall 5-min demands for each EV level. These calculations are given by equations 4 and 5.

$$d_{E5,l,i,j} = [l * d_{E5,i,j}] \ \forall \ i \in \text{month } j, \ l \in \text{EV levels} \quad (4)$$

$$d_{D5,l,i,j} = [d_{A5,i,j} + d_{E5,l,i,j}] \ \forall \ i \in \text{month } j, \ l \in \text{EV levels} \quad (5)$$

For the peak demand impact analysis calculations, the 5-min base level EV demands were scaled up by multiplying with whole number multiples as follows:

[25, 50, 75, 100, 200, 225, 250, 275, 300, 400, 600, 800, 1000, 1200, 1400].

6.1.4.1.3.2 Peak demand results formulation

The formulae for calculating the values of variables as described in table 4 for one replication set will be explained in this section.

Since peak demand is based on a 15-min time period, we calculated the 15-min rolling averages of the 5-min demands for circuit A and overall demands at different EV levels. This was done for each month starting day 1 at 00:00 hrs to last day at 23:55 hrs. These calculations are shown in equations 6 and 7.

$$d_{A15,i,j} = \left[\frac{\sum_{i}^{i+10min} d_{A5,i,j}}{3}\right] \ \forall \ i \in \text{month } j \quad (6)$$

$$d_{D15,l,i,j} = [\frac{\sum_{i}^{i+10min} d_{D5,l,i,j}}{3}] \; \forall \; i \in \text{month } j, \; l \in \text{EV levels} \tag{7}$$

From the 15-min rolling demands, the peaks for circuit A and overall demands at each EV level were calculated using equations 8 and 9.

$$D_{A15,j} = \max [d_{A15,i,j} \; \forall \; \text{month } j] \tag{8}$$

$$D_{D15,l,j} = \max [d_{D15,l,i,j} \; \forall \; \text{month } j], \; l \in \text{EV levels} \tag{9}$$

In addition, the times at which circuit A and overall peak demands occurred were noted at each EV level.

Equations 6, 7, 8 and 9 were applied to each replication month-wise, in the period July 2018 to June 2019. The average month-wise peaks and peak times for circuit A and overall demands for each EV level were then achieved by taking the averages of the peak demands and associated peak times obtained from the 15 replications of the respective months.

6.1.4.1.3.3 Peak demand overlap days formulation

Though we calculated the average month-wise peak for circuit A demand and overall demand at different EV levels, there would be other times of the day or days of the month which show high energy demand values with reference to a baseline value. This baseline can be referred to as the threshold value beyond which the energy demands would contribute as peaks to the demand profile. To explain this, we calculated baseline values by introducing demand limiting factors for circuit A and overall demand at each EV level. The values were individually calculated for every replication, month-wise in the duration July 2018 to June 2019. The demand limiting factors' calculations for circuit A and overall demands for all EV levels for one replication is given by equations 10 to 15 as developed in Saxena et al. (2019).

$$D_{limA,j} = [\mu_{A,j} + 2 * \sigma_{A,j}] \ \forall \text{ month } j \tag{10}$$

where:

$$\mu_{A,j} = [\sum_{i=1}^{n} \frac{d_{A15,i,j}}{n}] \ \forall \text{ i} \in \text{month j} \tag{11}$$

$$\sigma_{A,j} = [\sum_{i=1}^{n} \sqrt{\frac{(d_{A15,i,j} - \mu_{A,j})^2}{n}}] \ \forall \text{ i} \in \text{month j} \tag{12}$$

$$D_{limD} = [\mu_{D,j} + 2 * \sigma_{D,j}] \ \forall \text{ month } j \tag{13}$$

where:

$$\mu_{D,j} = [\sum_{i=1}^{n} \frac{d_{D15,l,i,j}}{n}] \ \forall \text{ i} \in \text{month j, l} \in \text{EV levels} \tag{14}$$

$$\sigma_{D,j} = [\sum_{i=1}^{n} \sqrt{\frac{(d_{D15,l,i,j} - \mu_{D,j})^2}{n}}] \ \forall \text{ i} \in \text{month j, l} \in \text{EV levels} \tag{15}$$

For every replication, the unique days in which a single or multiple 15-min rolling demands exceeded the demand limiting factors were identified. The unique circuit A peak days were then compared with unique overall peak days for each EV level. The days were then grouped as common peak demand days, unique circuit A peak demand days and unique overall peak demand days for each EV level. The average count of common peak and unique circuit A and overall peak days for each month was calculated by taking the average of the results obtained from the 15 replications. In addition, to arrive at the aggregate monthly unique overall peak days covering all EV levels, the average of average counts of overall unique peak days at each EV level was calculated.

6.1.4.2 Impact of increasing levels of EV demand on RIT's electricity charges

With increasing EV demand on RIT's circuit A, the impact on RIT's overall monthly electricity charges was analyzed. The monthly trend of total electricity charges and the month that reflects highest energy consumption charges and demand charges for increasing EV levels was determined. In addition, an average monthly permit fee for an EV user was determined for at each EV level.

6.1.4.2.1 Assumptions

- EV user contributes to offsetting RIT's monthly electricity charges by paying a monthly permit fee.
- Energy charge is applied based on the hourly average energy consumption i.e. kWh and demand charge, based on the 15-min rolling peak demand, i.e. kW.
- Energy charges and demand charges could vary monthly or seasonally based on the utility and regulatory market conditions.
- As EV infrastructure levels increase on campus, we assume the EV demand profiles to scale proportionally.

6.1.4.2.2 Notations

Table 6 provides a description of the variables used for carrying out the mathematical operations for EV impact analysis on RIT's electricity charges.

Table 6 Notations to carry out electricity charge calculations

Notation	Notation description	UoM
$Ec_{A,j}$	circuit A energy charge for month 'j'	$
$Ec_{D,l,j}$	overall energy charge for EV level 'l' and month 'j'	$
En_j	energy charge for month 'j'	$/kWh
$Dc_{A,j}$	circuit A demand charge for month 'j'	$
$Dc_{D,l,j}$	overall demand charge for EV level 'l' and month 'j'	$
Dm_j	demand charge for month 'j'	$/kW
$Tc_{A,j}$	circuit A total elec charge for month 'j'	$
$Tc_{D,l,j}$	overall total elec charge for EV level 'l' and month 'j'	$
$Y_{l,j}$	EV user fee for EV level 'l' and month 'j'	$
$\bar{y}_l$	avg. monthly EV user fee for EV level 'l'	$
n	base level EV users	nos.

6.1.4.2.3 Mathematical operations

For the electricity charges impact calculations, historic 5-min circuit A datafile and 5-min overall demands at each EV level as obtained from equation 5 were utilized. In addition, the 5-min base level EV demands were scaled up by multiplying with whole number multiples as follows:

[25, 50, 75, 100, 200, 225, 250, 275, 300, 400, 600, 800, 1000, 1200, 1400]

With current active 36 EV permits considered to be the base number of EV users on campus, EV level 800 corresponds with approximately 100% of RIT's population driving EVs. Levels 1000, 1200 and 1400 represent substantial campus growth. The current user occupancy on campus is around 23,000 with 19000 students and 4000 faculty members (RIT website, 2020). The approximate user count corresponding to level 800 is 28,800 which the is closest to the current population of 23,000.

Since RIT's negotiated electricity charges are confidential, the energy and demand charges as presented in Table 7 were used. The data is based on the conducted survey of various TOU pricing programs targeted at industrial customers of New York state (Wang, Y. et al., 2015).

Table 7 New York state electricity charges (Wang, Y. et al., 2015)

Months	En_j (\$/kWh)	Dm_j (\$/kW)
Jun - Sept	0.18815	19.41
Oct - May	0.13065	8.38

6.1.4.2.3.1 Energy charges

For each month, the historic 5-min circuit A and overall energy demands at each EV level was multiplied with the relevant energy charge as presented in Table 7. These calculations are shown in equations 16 and 17.

$$Ec_{A,j} = \left[\sum_{i=1}^{n} \frac{(d_{A5,i,j} * \mathrm{En}_j)}{12}\right] \ \forall \ i \in \text{month } j \tag{16}$$

$$Ec_{D,l,j} = \left[\sum_{i=1}^{n} \frac{(d_{D5,l,i,j} * \mathrm{En}_j)}{12}\right] \ \forall \ i \in \text{month } j,\ l \in \text{EV levels} \tag{17}$$

6.1.4.2.3.2 Demand charges

The month-wise circuit A and overall peak demands for increasing EV levels as expressed in equations 8 and 9 were multiplied with the relevant demand charge as presented in Table 6. These calculations are given by equations 18 and 19.

$$Dc_{A,j} = [D_{A15,i,j} * Dm_j] \ \forall \ i \in \text{month } j \tag{18}$$

$$Dc_{D,l,j} = [D_{D15,l,i,j} * Dm_j] \ \forall \ i \in \text{month } j,\ l \in \text{EV levels} \tag{19}$$

6.1.4.2.3.3 Total electricity charges

With the obtained monthly energy and demand charges as explained in sections 0 and 00, the total electricity charges for circuit A and overall demand for different EV levels were calculated using equations 20 and 21.

$$Tc_{A,j} = [Ec_{A,j} + Dc_{A,j}]\ \forall \text{ month } j \tag{20}$$

$$Tc_{D,l,j} = [Ec_{D,l,j} + Dc_{D,l,j}]\ \forall \text{ month } j,\ l \in \text{EV levels} \tag{21}$$

6.1.4.2.3.4 EV user permit fee

To calculate a monthly permit fee for an EV user, the portion of the total energy bill that EV charging accounts for, was determined. Using equation 22, the difference in total electricity charge for the overall demand at different EV levels with respect to circuit A for each month was calculated.

$$\delta\, Tc_{D,l,j} = [Tc_{D,l,j} - Tc_{A,j}]\ \forall \text{ month } j,\ l \in \text{EV levels} \tag{22}$$

The difference in total electricity charge obtained for each EV level was divided with the number of EV users on campus. With this, the fee for an EV user at each EV level for each month was obtained. This is given by equation 23.

$$Y_{l,j} = \left[\frac{\delta\, Tc_{D,l,j}}{n * l}\right]\ \forall \text{ month } j,\ l \in \text{EV levels},\ n \in \text{base count of EV users} \tag{23}$$

By calculating the month-wise average of the EV permit fees at every EV level, an overall monthly average EV user fee for each EV level was determined. This was calculated using equation 24.

$$\bar{y}_l = \left[\frac{\sum_{j=1}^{12} Y_{l,j}}{12}\right]\ \forall \text{ month } j,\ l \in \text{EV levels} \tag{24}$$

6.1.4.3 Impact of increasing levels of EV demand on RIT's circuit emissions

With increasing EV infrastructure on campus, the influence on the times during the day maximum emissions occur was understood. To determine the amount of carbon emissions based on emission factors, circuit A and overall demands at different EV levels were calculated on an hourly basis for each month in the duration July 2018 to July 2019. The calculations to study the impact of increasing EV demand on RIT's circuit emissions is explained in the following sub-sections.

6.1.4.3.1 Assumptions

- The amount of CO_2 emissions varies hourly through the day and monthly through the year.
- The CO_2 emissions associated with EV charging source mainly from electricity generation.
- The amount of CO_2 emissions at a certain time for a local system depends on the demand (kW) and type of fuel used to serve the demand (Siler-Evans, K. et al., 2012).
- Natural gas is the main fuel used to generate electricity in the North-east region of the U.S. (Siler-Evans. K. et al., 2012).
- Hourly emissions include average, maximum and minimum values and are measured using emission factors.
- As EV infrastructure levels increase on campus, we assume the EV demand profiles to scale proportionally.

6.1.4.3.2 *Notations*

Table 8 provides the information on variables considered for carrying out mathematical calculations for the EV impact analysis on RIT's system emissions. In addition, Table 9 provides the notation for average emissions factor that was retrieved from the 'Open Data Catalog' of the U.S. Department of Energy. (U.S. DOE, 2015).

Table 8 Notations to carry out monthly RIT system emissions calculations

Notation	Notation description	UoM
$d_{A,hh,d,j}$	circuit A demand for hour 'hh', day 'd' and month 'j'	kWh
$d_{D,hh,d,l,j}$	overall demand for hour 'hh', day 'd', for EV level 'l' and month 'j'	kWh
$d_{A,hh,j}$	hourly avg circuit A demand for month 'j'	kWh
$d_{D,hh,l,j}$	hourly avg overall demand for EV level 'l' month 'j'	kWh
$E_{Aavg,hh,j}$	circuit A avg emissions for hour 'hh' and month 'j'	$kgCO_2/kWh$
$E_{Davg,hh,l,j}$	overall avg emissions for hour 'hh', for EV level 'l' and month 'j'	$kgCO_2/kWh$
$\overline{E}_{Amax,hh,j}$	hourly avg circuit A max emissions for month 'j'	$kgCO_2/kWh$
$\overline{E}_{Aavg,hh,j}$	hourly avg circuit A avg emissions for month 'j'	$kgCO_2/kWh$
$\overline{E}_{Dmax,hh,l,j}$	hourly avg ovr demand max emissions for EV level 'l' and month 'j'	$kgCO_2/kWh$
$\overline{E}_{Davg,hh,l,j}$	hourly avg ovr demand avg emissions for EV level 'l' and month 'j'	$kgCO_2/kWh$

Table 9 Notations of emission factors data

	Notation description	UoM
$ef_{avg,hh,j}$	avg emissions factor for hour 'hh' and month 'j'	$kgCO_2/kWh$

6.1.4.3.3 *Mathematical operations*

For the circuit emissions impact calculations, historic 5-min circuit A datafile and 5-min overall demands for certain EV levels as obtained from equation 5 were utilized. In addition, the 5-min base level EV demands were scaled up by multiplying with whole number multiples as follows:

[50, 100, 200, 400, 800, 1400].

The hourly circuit A and overall energy demands at each EV level were calculated for each day month-wise in the duration July 2018 to June 2019. These calculations are shown in equations 25 and 26.

$$d_{A,hh,d,j} = [\sum_{i=hh:00}^{hh:55} \frac{d_{A5,i,j}}{12}] \ \forall \ i \in \text{day d and} \ \forall \ d \in \text{month j} \quad (25)$$

$$d_{D,hh,d,l,j} = [\sum_{i=hh:00}^{hh:55} \frac{d_{D5,l,i,j}}{12}] \ \forall \ i \in \text{day d and} \ \forall \ d \in \text{month j, l} \in \text{EV levels} \quad (26)$$

The hourly average circuit A and overall demands at each EV level were then calculated month-wise using equations 27 and 28.

$$d_{A,hh,j} = [\sum_{d=1}^{n} \frac{d_{A,hh,d,j}}{n}] \ \forall \ hh \in \text{day d and} \ \forall \ d \in \text{month j} \quad (27)$$

$$d_{D,hh,l,j} = [\sum_{d=1}^{n} \frac{d_{D,hh,d,l,j}}{n}] \ \forall \ hh \in \text{day d and} \ \forall \ d \in \text{month j, l} \in \text{EV levels} \quad (28)$$

Once the hourly average demands for each month were obtained, hourly emissions were calculated for each month based on the average emissions factor. These were obtained using equations 29 and 30.

$$E_{Aavg,hh,j} = [d_{A,hh,j} * ef_{avg,hh,j}] \ \forall \ \text{hour hh and} \ \forall \ \text{month j} \quad (29)$$

$$E_{Davg,hh,l,j} = [d_{D,hh,l,j} * ef_{avg,hh,j}] \ \forall \ \text{hour hh and} \ \forall \ \text{month j, l} \in \text{EV levels} \quad (30)$$

The month-wise aggregate maximum and average emissions for circuit A and overall demands at each EV level were finally calculated using equations 31 to 34.

$$\overline{E}_{Amax,hh,j} = \max [E_{Aavg,hh,j} \ \forall \ hh \in \text{month j}] \quad (31)$$

$$\overline{E}_{Aavg,hh,j} = [\sum_{hh=1}^{24} \frac{E_{Aavg,hh,j}}{24}] \ \forall \ \text{month j} \quad (32)$$

$$\overline{E}_{Dmax,hh,j} = \max [E_{Davg,hh,j} \ \forall \ hh \in \text{month j}], \ l \in \text{EV levels} \quad (33)$$

$$\overline{E}_{Davg,hh,j} = [\sum_{hh=1}^{24} \frac{E_{Davg,hh,l,j}}{24}] \ \forall \ \text{month j, l} \in \text{EV levels} \quad (34)$$

7 Results and Discussion

In this section, the findings and observations obtained from the analyses as mentioned under the Problem Statement will be presented.

7.1 Impact of increasing levels of EV demand on circuit A peak demand

With the existing base level EV demand, the impacts of increasing EV levels starting 25, 50 and so on up to 1400 were analyzed on circuit A's monthly peak demand. The month-wise results explained in this sub-section is based on the average results obtained from the 15 replications of the respective months.

Table 10 provides the peak month demand trend for the duration July 2018 to June 2019 for increasing EV levels.

Table 10 Peak month demand data for increasing EV levels

Network	Peak month	Peak Demand (kW)	Peak Time (hh:mm)
Ckt A 0 EV	Sep-18	8215.67	16:40
Overall base EV	Sep-18	8219.37	16:40
Overall 25 EV	Sep-18	8336.94	16:40
Overall 50 EV	Sep-18	8647.27	15:20
Overall 75 EV	Sep-18	9170.99	15:20
Overall 100 EV	Sep-18	9807.84	9:55
Overall 200 EV	Sep-18	12452.40	9:55
Overall 225 EV	Sep-18	13129.88	9:55
Overall 250 EV	Feb-19	13867.22	9:20
Overall 275 EV	Feb-19	14749.28	9:20
Overall 300 EV	Feb-19	15631.33	9:20
Overall 400 EV	Feb-19	19160.71	9:20
Overall 600 EV	Feb-19	26225.33	9:20
Overall 800 EV	Feb-19	33294.60	9:20
Overall 1000 EV	Feb-19	40365.27	9:20
Overall 1200 EV	Feb-19	47437.53	9:20
Overall 1400 EV	Feb-19	54510.87	9:20

Initially, the overall peak demand occurs in the month of Sept 2018 up to EV level 225. The trend shifts to Feb 2019 at EV level 250 and continues to show peak demand up to EV level 1400. This means that as the EV demand level reaches 250 times the base level, the overall network gets significantly loaded in the month of February. The average monthly overall peak time shift from circuit A peak demand is presented further in this section. Figure 4 depicts the shift in peak demand trend from Sept 2018 to Feb 2019.

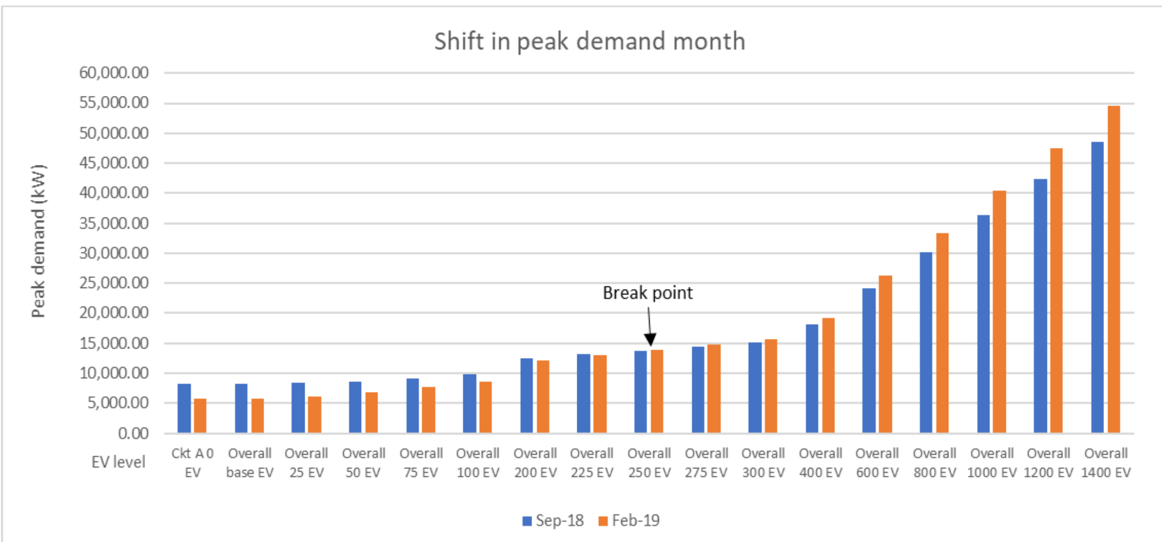


Figure 4 Shift in peak demand trend

September proves to be an active month in the Fall season with classes, labs and work schedules throughout campus. However, with increasing EV levels beyond level 225 the effects of vehicle charging demand supersedes the effect of circuit A's energy demand and is observed in February. Moreover, with February lying in peak winter period the amount of solar energy generated could be relatively low. Due to this, more energy for EV charging would be drawn from the grid, thereby loading circuit A network. The shift in peak demand month is reflected in the increase in number of overall peak demand days which is discussed shortly, further in this section. Apart from considering the maximum electricity consumption in the month of Sept 2018, once EV level reaches 225 times the base level RIT should plan on focusing implementing load planning strategies in February to accommodate increasing EV demand and maintaining a leveled overall demand profile.

In relation with peak demand occurrence, Figure 5 shows the month-wise average peak demand times for circuit A and overall demands for increasing EV levels. Figure 5 also depicts the average daily shift in overall peak demand time from circuit A's, for the overall period July 2018 to June 2019.

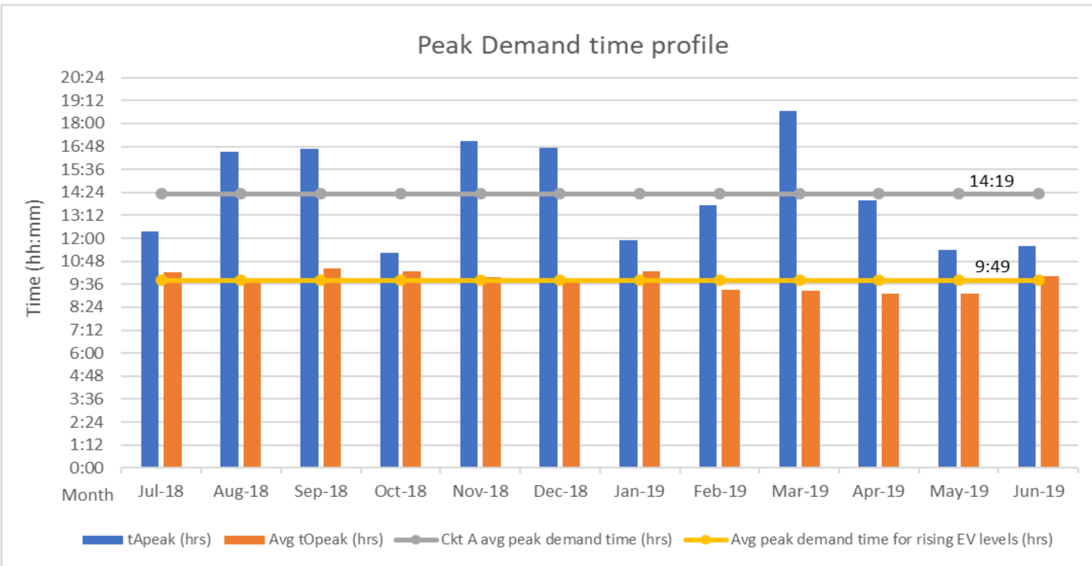


Figure 5 Average peak demand time occurrence – Month-wise and overall period

The blue colored bar chart series illustrates the month-wise average circuit A peak demand times. The orange bar chart series represents the month-wise average overall peak time for increasing EV levels. Most months in the period July 2018 to June 2019 experience circuit A peak demand in the afternoon. However, months October, May and June are exceptions. The monthly average circuit A peak demand time is shown by the grey horizontal line which corresponds to 14:19 hrs, i.e. 2:19 p.m. The monthly average peak demand time shifts to morning hours as the EV demand on circuit

A’s network increases. The average shift in overall peak demand time is shown by the yellow horizontal line and corresponds to 9:49 hrs (a.m.). March, November, December, August and September show significant peak demand time shifts from evening to morning hours. The pictorial representation of time shifts for these months is shown in Figure 6. To summarize, with an increase in EV demand the overall peak demand time frame shifts from afternoon to morning hours with an average shift by 4.5 hours, i.e. (14:19 – 9:49) hrs. Circuit A and overall peak times for each EV level are presented in Table 11.

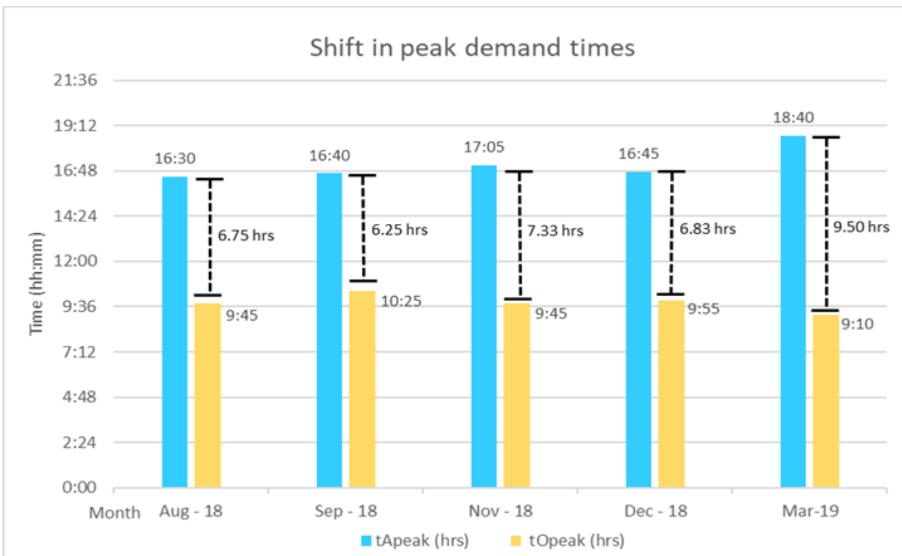


Figure 6 Maximum shifts in peak demand times

Table 11 Average peak time for increasing EV levels

EV level	Avg. peak time (hh:mm)
Circuit A 0 EV	14:19
Overall base EV	14:18
Overall 25 EV	12:11
Overall 50 EV	11:15
Overall 75 EV	10:37
Overall 100 EV	10:21
Overall 200 EV	9:52
Overall 225 EV	9:50
Overall 250 EV	9:49
Overall 275 EV	9:48
Overall 300 EV	9:49
Overall 400 EV	9:47
Overall 600 EV	9:48
Overall 800 EV	9:47
Overall 1000 EV	9:48
Overall 1200 EV	9:48
Overall 1400 EV	9:48

From Table 11, it can be observed that the average original peak time which occurs during afternoon hours shifts to morning at EV level 50. Considering majority morning class and work schedules, students and faculty with EVs would tend to plug in their vehicles as soon as they arrive on campus in the morning. Also, with gradually increasing EV levels the users could be subjected to competition anxiety for gaining full access to EV charging stations. These probabilities could influence the EV charging times at level 50 and onwards, thereby concentrating RIT's circuit load to morning hours.

With the anticipation of peak time occurring during morning hours, RIT may have to implement EV charging policies by which the total EV demand is distributed through the workday. By incentivizing EV users for charging vehicles at designated times, the overall demand profile could be well maintained.

Table 12 provides the month-wise count of total circuit A peak days, aggregate total overall peak days for all EV levels from 25 up to 1400 and overlap days. The month-wise aggregate total overall peak days count entails all EV levels since the total overall peak days remains nearly the same through all EV levels from an average level of 200. As an example, consider Figure 7 which shows the trend of total overall peak days count for increasing EV levels for July 2018.

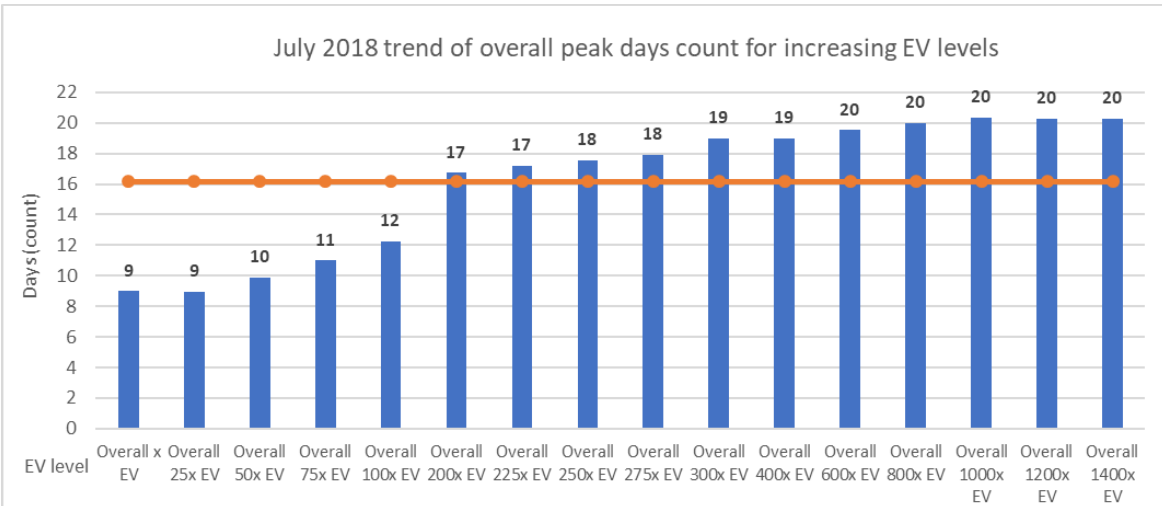


Figure 7 Trend of overall peak days count for July 2018

From Figure 7, it is observed that the overall peak days count at lower EV levels increases gradually. The change in trend is observed at EV level 200 where the count remains nearly the same with an average of 16 as depicted by the orange trend line.

Table 12 Month-wise split of overlap and new overall peak demand days

Month	Tot D_{A15} days count	Aggr. Tot $D_{D15,l}$ days count	Overlap days	% Overlap days with D_A days	New $D_{D15,l}$ days count
Jul-18	9	16	7	77.78%	9
Aug-18	7	17	5	71.43%	12
Sep-18	6	14	4	66.67%	10
Oct-18	7	17	4	57.14%	13
Nov-18	0	15	0	0.00%	15
Dec-18	4	13	4	100.00%	9
Jan-19	5	18	5	100.00%	13
Feb-19	1	17	1	100.00%	16
Mar-19	9	19	8	88.89%	11
Apr-19	8	20	7	87.50%	13
May-19	10	18	8	80.00%	10
Jun-19	6	13	4	66.67%	9

In addition to days counts, Table 12 also provides the month-wise percentage of overlap days relative to number of total circuit A peak days. Nearly all months in the duration July 2018 to June 2019 are observed to have a significant percentage of circuit A peak days persisting as peak days with additional EV demand. With increasing EV levels, months Nov 2018 and Feb 2019 show the highest number of new overall peak days, i.e. 15 and 16 respectively. Furthermore, Nov 2018 is the only month which does not show any circuit A peak days with reference to the demand limiting factor as explained in section **Error! Reference source not found.**. The pictorial representation of months showing maximum peak overlap days and maximum new overall peak days for increasing EV levels is shown in Figures 8 and 9 respectively.

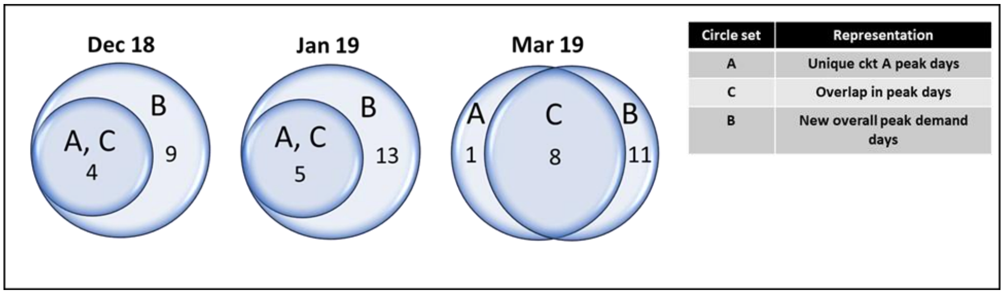


Figure 8 Months with maximum peak days overlap

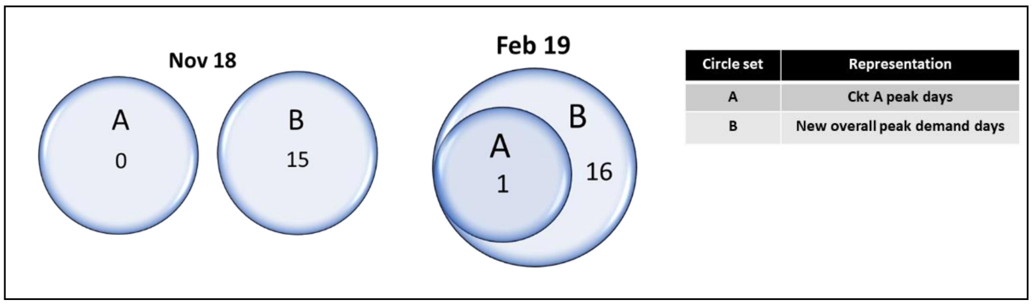


Figure 9 Months with maximum new overall peak demand days

The introduction of maximum new overall peak days means that RIT's network is significantly influenced even at lower levels of EV penetration in the months November and February. With this observation it could be inferred that circuit A in months November and February is just enough loaded, that additional EV demand drives the network into peak load conditions.

Though November and February showed the maximum count of new overall peak days for the aggregated EV levels, the extent by which the average month-wise peak demands significantly exceed the corresponding average demand limiting factors were reflected in other months. Up to EV level 100, Oct 2018 showed the maximum difference in the average overall peak demand and the average demand limiting factor. At EV level 200 and beyond, the maximum difference in the average overall peak demand and the corresponding demand limiting factor was reflected in Dec 2018. Oct 2018 is represented by the yellow bar chart series and Dec 2018, by the green bar chart series. The shift is illustrated in Figure 10.

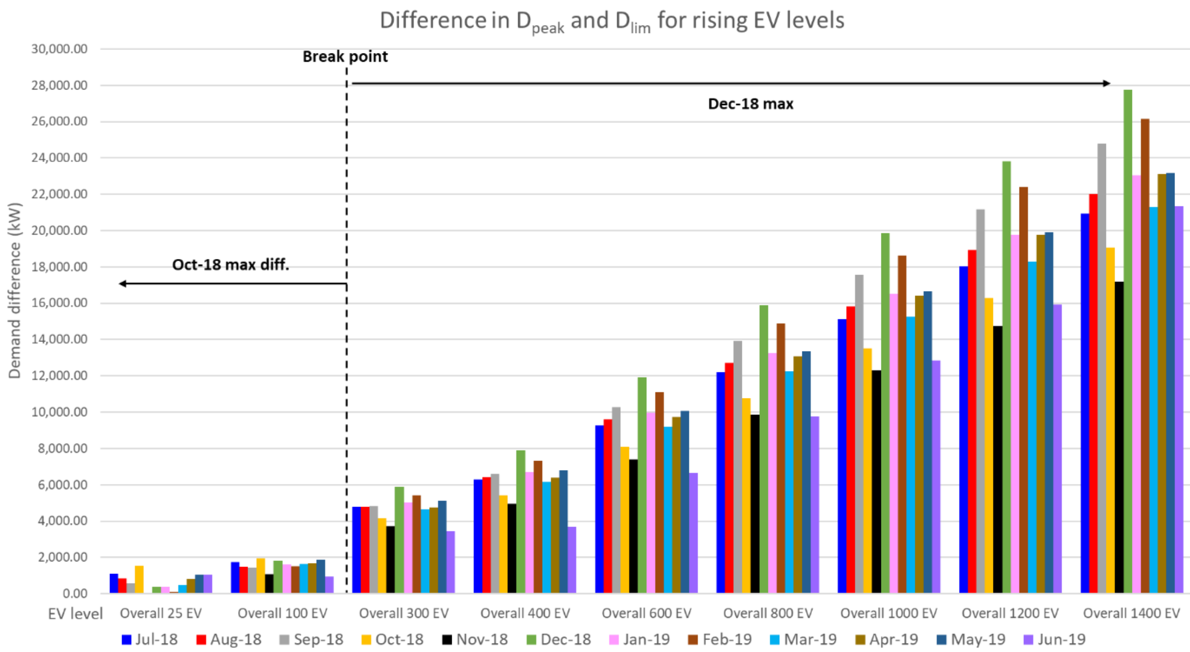


Figure 10 Trend of maximum difference in overall peak demands and demand limiting factors at different EV levels

October lies in the middle of the Fall semester and is usually an active campus period. Being a busy month, the October break during which there are no classes or labs scheduled may influence the month's demand limiting factors at lower EV levels to be relatively lower compared to other months. Also, the effects of high energy demand on normal working days during the month seems to influence the gap between the demand limiting factors and respective overall peak demands at lower EV levels. The trend shifts to December as circuit A is loaded with higher EV level demands. December break which is usually a span of about 25 days seems to similarly influence the large gap between the overall peak demands and the relative demand limiting factors. With increase in EV demand but low campus load demand, the effects of EV demand tends to overpower the impacts on circuit A's network.

The results obtained under this impact category was assumed on the basis that EV infrastructure on campus increases in proportion with the increase in EV levels. However, the installation of new charging stations for every increase in count of EV users is not a practical scenario. Several factors such as campus space utilization, electrical network capacity, existing energy usage, institution’s legal conditions, monetary investments, etc. would influence the installation of new EV infrastructure. However, the assumption was taken into consideration to present the worst-case scenario wherein enough charging capacity is available for every incoming EV user. In addition, there is no restriction in the use of charging stations for the EV users. Without assuming an increase in EV infrastructure, the peaks in the overall demand would not necessarily be high. This would be on account that all charging stations will already be in use thereby, creating a bottleneck for access to vehicle charging by many other EV users. This would end up in many EV users left without getting their vehicle charged. If the current count of 11 EV charging stations is considered for increasing levels of EV demand and user count, the overall impacts on circuit A would be different.

7.2 Impact of increasing levels of EV demand on RIT’s electricity charges

After calculating the electricity charges as explained in section 6.1.4.2.3, the results can be grouped under energy charges, demand charges and total electricity charges. The following sub-sections will elaborate these results.

7.2.1 Energy charges

August shows the maximum energy charges for circuit A and overall demand for increasing EV levels up to 100. At EV level 200 and above, the maximum energy charge is observed in the month of September. The shift is depicted in Figure 11.

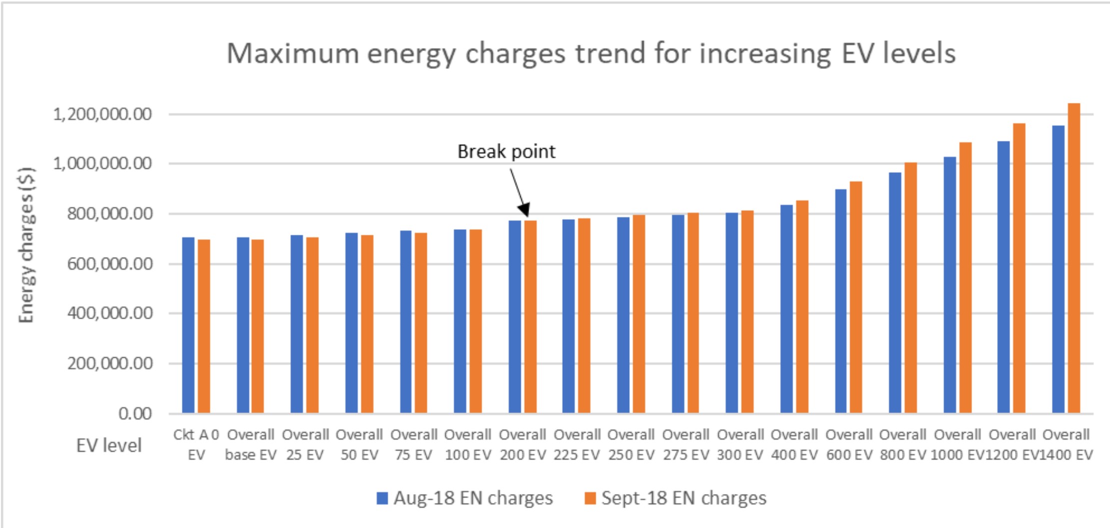


Figure 11 Shift in maximum energy charges trend

In the beginning of the Fall semester starting August, circuit A would mostly be loaded because of significant usage of amenities on account of high inflow of newly admitted students. Also during end August and the entire month of September, class and work schedules are very busy. In addition to the lighting and HVAC load, the energy consumption would further increase due to EV charging. As a result, high energy charges could be expected in the months August and September.

7.2.2 Demand charges

The month showing maximum demand charges fluctuates between months August and September until EV level 400. Beyond EV level 400, the maximum demand charge is observed in the month of September. This observation is shown in Figure 12.

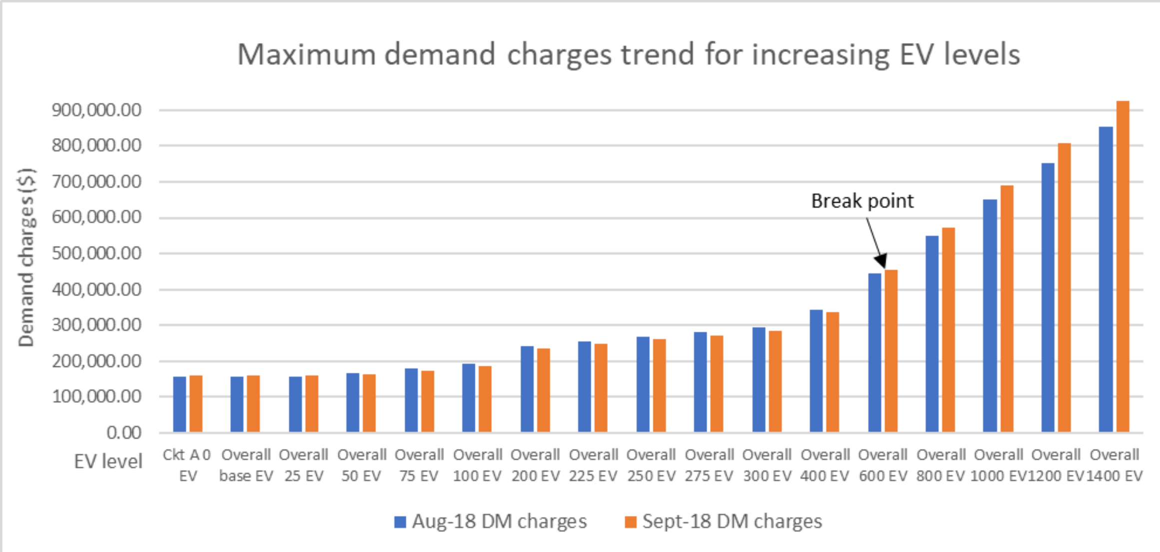


Figure 12 Maximum demand charges trend

In line with high energy usage and associated energy charges, the circuit's peak demand is apparent in the month of September when the overall load is prominent during the year. The associated demand charges are reflected in the trends of circuit A and overall demands at different EV levels.

7.2.3 Total electricity charges

August shows the maximum total electricity charges up to EV level 250. The trend shifts to September at EV level 275 and above. Figure 13 depicts the shift in maximum total electricity charges.

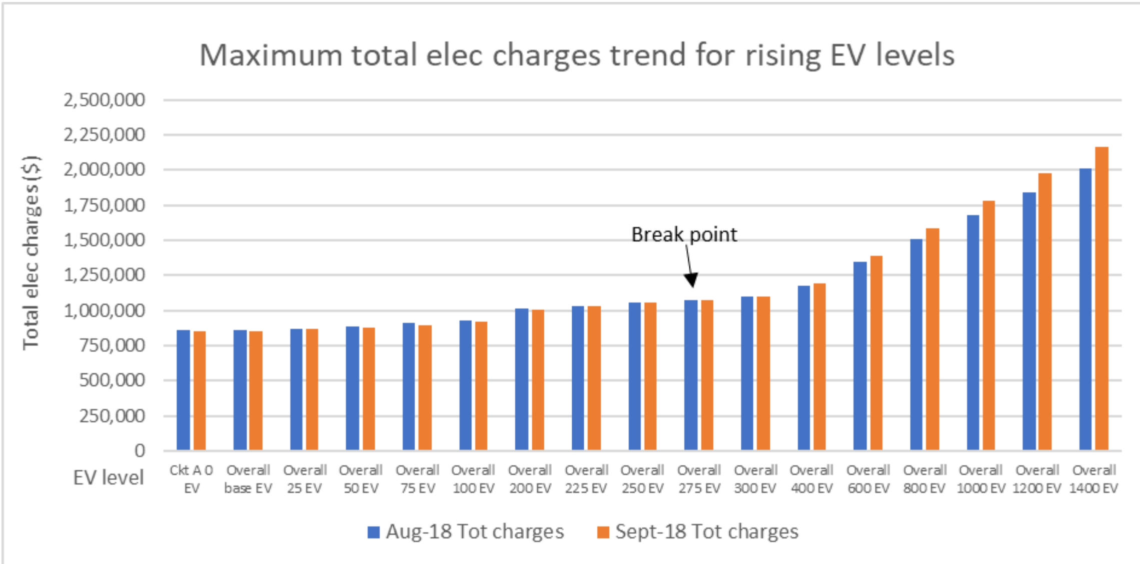


Figure 13 Maximum total electricity charges trend

To summarize, months August and September show higher electricity charges for circuit A demand and overall demands for increasing EV levels.

In addition to load planning in the month of February which marks the peak month at higher EV levels, RIT should maintain existing demand response strategies for September to reduce high demand charges.

7.2.4 EV user permit fee

As explained in section 6.1.4.2.1**Error! Reference source not found.**, we have assumed that EV users contribute towards RIT's monthly electricity bills. To understand what the current and future contribution is, we calculated the electricity charges applied solely from EV charging demand.

Table 13 provides the month-wise calculated EV fee for base EV level on campus.

Table 13 Month-wise EV user fee for base EV level

Month	EV total elec charges ($)	Base EV level user fee Y ($)
Jul-18	554.12	15.39
Aug-18	339.85	9.44
Sep-18	416.66	11.57
Oct-18	449.49	12.49
Nov-18	337.74	9.38
Dec-18	293.80	8.16
Jan-19	442.86	12.30
Feb-19	404.53	11.24
Mar-19	354.77	9.85
Apr - 19	408.12	11.34
May-19	445.29	12.37
Jun-19	494.55	13.74
Avg	411.81	$\bar{y}$ = 11.44

We can observe that with base EV level on campus where number of EV users is 36 (n=36), the average monthly fee '$\bar{y}$' is $11.44. With increasing EV levels on campus, the impact on average monthly EV fee is shown in Table 14.

Table 14 Average monthly EV fee for increasing EV levels

EV level	No. of EV users (n*l)	$\bar{y}_l$	% increase in avg EV fee from base level EV
Overall base EV	36	11.44	---
Overall 25 EV	900	12.53	9.53
Overall 50 EV	1800	13.88	21.33
Overall 75 EV	2700	14.88	30.07
Overall 100 EV	3600	15.51	35.58
Overall 200 EV	7200	16.74	46.33
Overall 225 EV	8100	16.92	47.90
Overall 250 EV	9000	17.07	49.21
Overall 275 EV	9900	17.18	50.17
Overall 300 EV	10800	17.28	51.05
Overall 400 EV	14400	17.57	53.58
Overall 600 EV	21600	17.93	56.73
Overall 800 EV	28800	18.10	58.22
Overall 1000 EV	36000	18.21	59.18
Overall 1200 EV	43200	18.28	59.79
Overall 1400 EV	50400	18.33	60.23

Table 14 covers average EV permit fee at each EV level up to 1400. At EV level 75 the first significant relative increase in monthly EV permit fee from base EV level is observed i.e. nearly 30%, followed by at level 200, i.e. increase by nearly 46%.

With increasing EV users on campus, the average fee per user should increase since RIT's monthly demand charge becomes a prominent component of the total electricity charge as the overall demand increases. Without demand charge, the EV user would be paying just for energy consumed for vehicle charging. In turn, the permit fee would remain the same even though the EV users increase on campus. As EV demand increases on circuit A's network, with application of optimal monthly EV permit fee and appropriate vehicle charging techniques, demand profiling could be managed to attain healthy network operation.

The permit fee values for increasing EV levels as seen in Table 14 is based on the proportional increase in EV user count for every scale up in EV demand. There are predictions that by the year 2030, about 7% of the vehicles on the U.S. roads would be EVs (Edison Electric Institute, 2018). Applying this prediction, 7% would correspond to 1610 EV users out of RIT's population of 23,000 by the year 2030. The 1610 count of EVs nearly matches the total EV user count of 1800 at EV level 50. This means that the EV permit fee from the current value of $11.44 in the year 2020 should increase to $13.88 by the year 2030. Considering this 10-year time frame, RIT should utilize resources and consider carrying out various strategies and modeling techniques for vehicle charge time-scheduling for increasing EV users on campus. This would facilitate robust and ready to implement strategies for load profile handling by the year 2030 which could further influence the electricity charges and thereby, EV permit fee price.

Figure 14 shows circuit A demand trend for two consecutive days of Feb 2019. As highlighted, circuit A peak demand occurred in the afternoon at 12:45 p.m. on 27th Feb 2019. Figure 15 illustrates the overall demand profile at EV level 50 for the same two consecutive days. In this case, the overall peak demand at EV level 50 occurred in the morning at 9:20 a.m. on 26th Feb 2019.

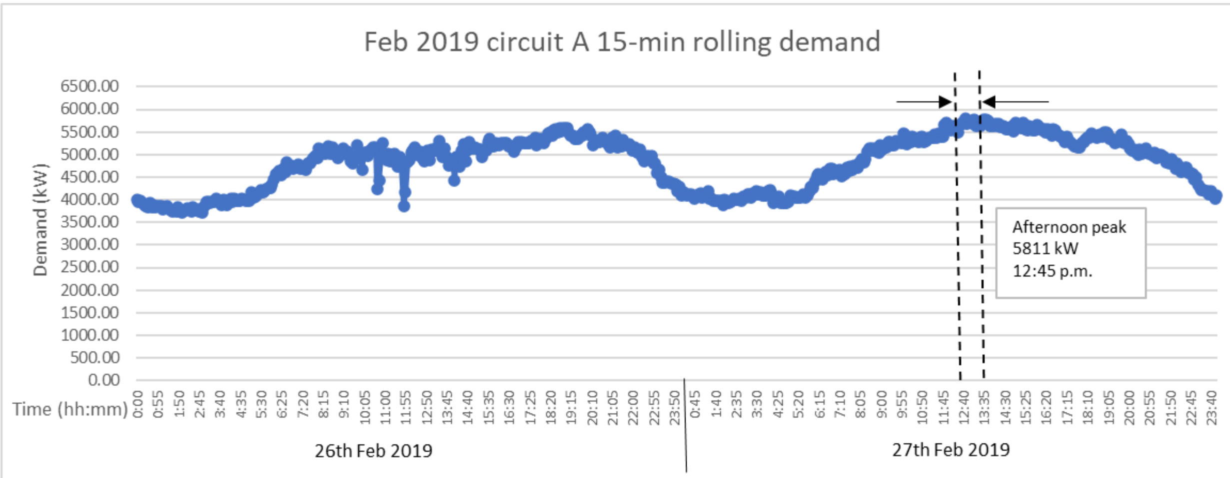


Figure 14 Circuit A demand trend 26th – 27th Feb 2019

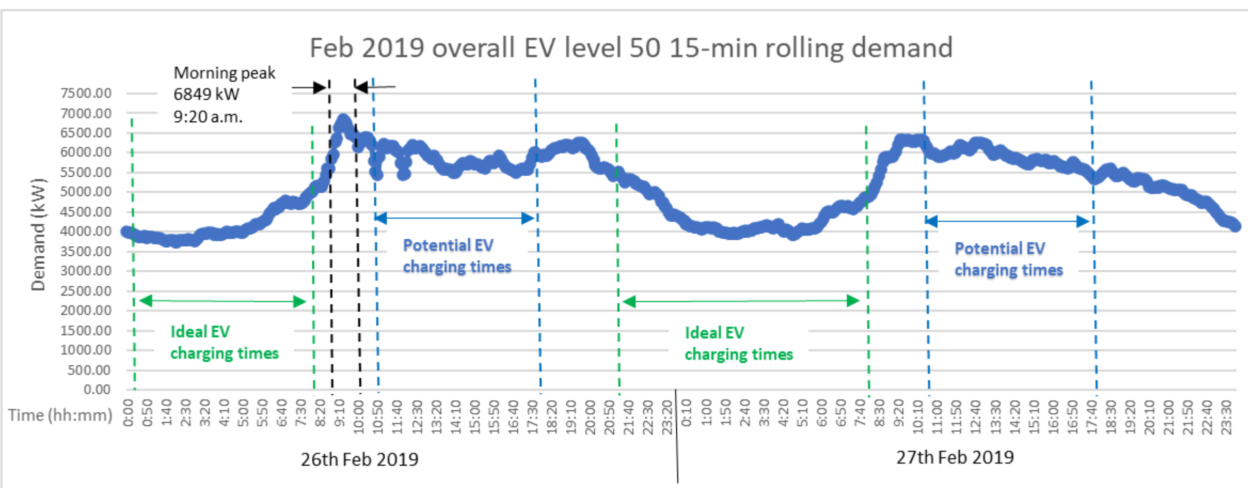


Figure 15 Overall EV level 50 energy demand trend 26th – 27th Feb 2019

As illustrated in Figure 15 to manage the morning overall peak demand at EV level 50, the ideal EV charging times through the entire day lie mainly in the time period: around night 8:30 p.m. to morning 8:00 a.m. on the next consecutive day. However, EV users are not expected to carry out vehicle charging during mid-night hours. Potential to achieve a better demand profiling through the day is by incentivizing EV users on campus to charge their vehicles during the duration: morning 10 a.m. to evening around 6 p.m. Within this time duration the overall demand can be distributed, thereby avoiding peaks to the overall demand profile through the workday. This will in turn reduce RIT's monthly electricity charges that could influence to lower the monthly permit fee applied to EV users on campus.

7.3 Impact of increasing levels of EV demand on RIT's circuit emissions

Results on the month-wise average and maximum emissions trend will be presented in this section. In addition, the average hour of the day during which maximum emissions occur at different EV levels will be shown. This will give the reader an idea about an appropriate time of the day for vehicle charging with the objective to avoid additional circuit emissions caused from EV charging.

It was observed that, with increasing levels of EV demand, the month of maximum emissions shifts from October to April. However, October is the month which persistently shows highest daily average emissions throughout the duration July 2018 to June 2019. In addition, the time of day during which maximum emissions occur shifts from evening hours to morning hours with increase in EV levels. Table 15 shows the month-wise hour of the day maximum emissions occur at different EV levels. In addition, Figure 16 illustrates the average shift in hour of the day maximum emissions occur.

Table 15 Month-wise hour of maximum emissions at different EV levels

EV level	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Avg hour of day
Ckt A 0 EV	20	14	19	19	18	17	16	19	21	21	21	20	19
Ovr base EV	20	14	19	19	18	17	16	19	21	21	21	20	19
Ovr l 50 EV	11	14	19	11	18	11	11	10	10	10	10	10	12
Ovr l 100 EV	11	11	11	11	11	11	11	10	10	10	10	10	11
Ovr l 200 EV	11	11	11	11	11	11	11	10	10	10	10	10	11
Ovr l 400 EV	11	10	11	11	11	11	11	10	10	10	10	10	11
Ovr l 800 EV	11	10	11	11	10	11	11	10	10	10	10	10	10
Ovr l 1400 EV	11	10	11	11	10	11	11	10	10	10	10	10	10

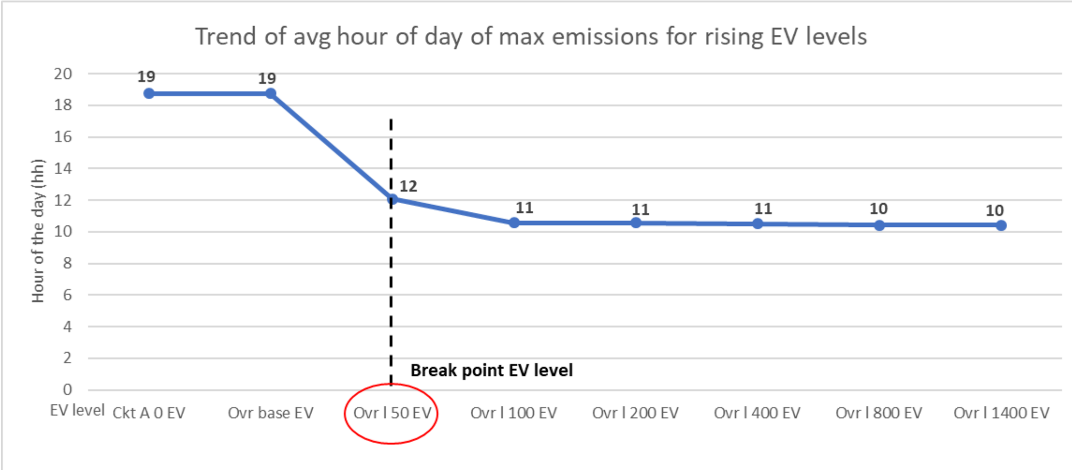


Figure 16 Shift in hour of maximum emissions for increasing EV levels

The average time of day during which maximum emissions occur shifts from evening, between 7 p.m. and 8 p.m. (19^{th} hour) to morning, between 10 a.m. and 11 a.m. (10^{th} hour) at EV level 50 and above.

System emissions and overall peak time trends, both seem to change at EV level 50. With average shift in overall peak time and high system emissions from evening to morning hours, the overall system seems to be burdened during the time window 9 a.m. to 11 a.m. Implementing EV charging strategies as suggested in section 7.2.4, would facilitate leveled demand profiling. This would in turn lead to a reduction in system emissions and reduced electrical burden on RIT's network caused by additional EV demand.

8 Conclusion and Future work

This paper has reviewed the impacts of increasing EV demand on RIT circuit's energy demand profiles, potential EV related electricity costs and system emissions. With this, the following points can be concluded and can serve as implications that RIT needs to take into consideration.

The behavior of the overall demand profile noticeably changes at EV level 50 when the peak time shifts from afternoon to morning hours. In addition, with further increase in EV levels the peak month changes from Fall semester month September to Spring semester month February as EV level reaches 250. In line with peak demand profile, the overall high electricity charges are consistently seen in months August and September with September being more prominent at EV level 275 and above. The nearest significant permit fee increase will occur when EV level reaches 75 times the base level. Moreover, the increase in EV permit fee will be on account of higher demand charges for increasing levels of EV demand. However, as mentioned in section 7.2.4 EV level 50 corresponding to 1800 EV users is about 7% of the total RIT's population which is expected to occur by year 2030. Lastly, system emissions are observed to increase during the daytime when EV level reaches 50. With these summarized observations, RIT needs to take steps for accommodating the future increase in EV demand. As new EV users get registered on campus, the existing electrical network should be prepared to operate the EV charging with causing no power interruptions. In order to achieve this, implementation of appropriate demand response strategies including incentivizing EV users for not plugging in their vehicles as soon as they arrive to campus should be done. As the user count approaches 50 times the base count, i.e. EV level 50 RIT's management should be technically and monetarily equipped for carrying out the load planning operations as the year 2030 approaches. This will facilitate a healthy electrical network and thereby lower demand charges billed to the institution and potentially reduce overall emissions.

In this thesis paper the overall demand profile of circuit A is scaled in line with increasing EV demand at several EV levels. This may not be a fair assumption as demand profile could be influenced by many variable factors such as population dynamics, network dynamics, seasonal dynamics, institutional policy dynamics, general trend of growing EV sales, etc. Detailed impact analysis of different EV charging policies at EV levels below 50 could be evaluated on RIT's demand profile and monthly electricity billing. This could help RIT anticipate immediate effects of increasing EV demand on the network and address the concerns by carrying out the appropriate actions. Moreover, time scheduling of EV charging during lower demand hours during the workday is an area that needs detailed analysis.

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